Fintech and Racial Barriers in Small Business Lending

Celine Yue Fei
Kenan-Flagler Business School, University of North Carolina at Chapel Hill
Keer Yang
Carlson School of Management, University of Minnesota

First Draft: May 31, 2021
This Version: October 26, 2021

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Abstract

Using a linked database of Paycheck Protection Program (PPP) loans and Yelp-listed restaurants, we document that businesses owned by minority racial groups are more likely to use fintech lenders than traditional lenders. We develop a simple two-sided matching model to show that this phenomenon can be generated by differences in performance among borrowers, racial disparities in lending relationships, and race-dependent values of borrower-lender matches. We do not find consistent evidence that operational performance is an explanation. We find supporting evidence that minority-owned restaurants are less likely to have lending relationships and that restaurants without lending relationships are more likely to use fintech lenders. We also find a more negative minority-non-minority gap in operational performance for fintech lenders, suggesting minority-owned businesses have higher matching values with fintech lenders. We do not find a similar pattern for first-time bank participants, community development financial institutions, credit unions, or other non-federally insured lenders. Overall, our results suggest that there are racial barriers in traditional loan distribution channels and this can be at least partially addressed by fintech lenders.

Keywords: Racial Barriers, Minority-owned Businesses, Paycheck Protection Program, Small Business Lending, Bank Lending, Nonbank Lending, Fintech.

JEL No. D63, G2, G21, G28, H25, M14

* Celine_Fei@kenan-flagler.unc.edu, yang5427@umn.edu. We would like to thank Yasser Boualam, Gregory W. Brown, Ulrich Hege, Paige Ouimet, Elena Simintzi, Jeremy C. Stein, Boris Vallée, and participants at the brownbag workshops at Minnesota and UNC, and the UNC entrepreneurship working group workshop for very helpful comments. Thanks to Cecilia Poston and Xueya Luo for excellent research assistance. All errors are our own. We gratefully acknowledge financial support from the Kenan Institute Small Research Grant (Fei).

1. Introduction

It has been long documented that minority-owned businesses are less likely to access the traditional credit market (Bates, 1997; Tareque et. al., 2021).[1] More recent evidence shows that fintech companies and online banks are increasingly utilized by minority-owned businesses (SBCS, 2021), even when the government removes all credit risk from lenders (Erel and Liebersohn, 2020). However, empirical studies are scarce on whether this is due to economic barriers or statistical discrimination (Becker, 1957; Arrow, 1971; Phelps, 1972), probably because of the lack of data on small business lending.

In this paper, we attempt to fill the gap by providing novel evidence for the following question: are fintech lenders more popular among minority-owned businesses simply because of differences in their operational performance per se, or because minority-owned businesses face higher barriers at traditional lenders? Because fintech lending largely reduces in-person interactions, thus reducing opportunities for racial barriers, it is plausible that minority borrowers would prefer fintech lenders because they provide more value to them.

We answer this question by exploiting the unique design of the Paycheck Protection Program (PPP), a key component of the Coronavirus Aid, Relief, and Economic Security (CARES) Act enacted on April 3, 2020.[2] It provides a laboratory in which to study this question for several reasons. First, the loan terms are fixed by the Small Business Administration, which rules out that fintech lenders attract different borrowers because of more flexible loan terms. Second, all small businesses are hit by the Covid-19 shock almost simultaneously, and applications start on the same day for all borrowers. This controls for the impact of the business development stage on fintech usage. Third, the entry of fintech lenders is largely driven by the sudden demand for loan processing in the pandemic. This mitigates supply-side endogeneity concerns as fintech lenders target a specific segment of minority borrowers. Fourth, as discussed in several papers (Amiram, and Rabetti, 2020; Balyuk, Prabhala, and Puri, 2020; Duchin et. al., 2021), the credit risk concern

[1] Other papers include Cavalluzo and Cavalluzo (1998), Cavalluzzo, Cavalluzzo, and Wolken (2002), Blanchflower, Levine, and Zimmerman (2003), Cavalluzzo and Wolken (2005), Blanchard, Zhao, and Yinger (2008), Asiedu, Freeman, and Nti-Addae (2012), and Bates and Robb (2013, 2015). Additionally, Cherry et. al. (2021) find that borrowers in minority-dominated regions were more likely to obtain debt relief during the Covid-19 pandemic.

[2] More information on the PPP program is provided in the Appendix. See also https://www.sba.gov/funding-programs/loans/covid-19-relief-options/paycheck-protection-program

is fully transferred to the government in the PPP. Thus, differences in the use of fintech lenders by minority and non-minority borrowers cannot be explained by the risk management of lenders.

In addition, the PPP provides a unique dataset that covers a segment of borrowers that, under normal circumstances, are impeded by high barriers to credit market access and thus do not appear in conventional loan application datasets. However, since the Covid-19 crisis is an economy-wide shock, the high demand for credit, plus the extremely low interest rate and the possibility of forgiveness, provides strong incentives for any borrower to participate.[3]

We start by documenting racial disparities in the PPP, using our nationwide sample of over 98,000 Yelp-listed restaurants linked to first-draw recipients in 2020 and 2021.[4] The results are consistent with the existing literature. Figure 1 shows that in 2021, non-fintech lenders deliver more loans to non-minority-owned businesses (Figure 1(a)). In contrast, there is not a clear minority-non-minority gap for fintech lenders (Figure 1(b)). In our regression analysis, we also find a positive relationship between fintech usage and minority-owned businesses.

Next, we develop a simple two-sided matching game model to understand the mechanisms leading to this phenomenon. First, even in equilibrium without racial disparities in the lending market, our model predicts that a positive (negative) correlation between operational performance and fintech usage,[5] combined with minority-owned businesses with better (worse) operational performance, can generate the phenomenon that more minority-owned businesses use fintech lenders. Second, the existing literature shows that lending relationships have a large impact on the priority of borrowers in the queue in the PPP (Li and Strahan, forthcoming; Amiram, and Rabetti, 2020; Duchin et. al., 2021). Given that borrowers without bank lending relationships face a crowding-out effect by borrowers with lending relationships, our model predicts that if fewer minority-owned businesses had lending relationships in the pre-Covid period, more of them would turn to fintech lenders. Third, when the *value* of the borrower-lender match is race-dependent, our model also predicts a higher fintech usage for minority-owned businesses, even without a difference in operational performance or the proportion of borrowers having lending relationships.

[3] Admittedly, some borrowers might be rejected after the loan application, but the survey results in Bartik et. al. (2021) suggest that inability to submit an application accounts for two-thirds of the loan denials and in total only 8% of the loan applications are rejected by the SBA.
[4] The first draw refers to first-time loans applied for by borrowers in 2020 and 2021. The second draw refers to the re-application of a second loan in 2021.
[5] Even in a fully government-guaranteed loan program, fintech usage can correlate with the borrower's operational performance due to businesses of better operational performance self-selecting into fintech lenders or lower performance borrowers who have bank lending relationships crowding out other borrowers to fintech lenders.

In reality, the *value* of technology can be different for minority and non-minority borrowers, leading to racial barriers in the lending market.

One distinct feature of the third case is that we observe a difference in the minority-non-minority operational performance gap between those using fintech and non-fintech lenders (i.e. a double difference in the operational performance). This prediction does not hold in the first two cases. Empirically, based on this insight, if we find evidence of a more negative minority-non-minority operational performance gap for fintech lenders, this implies that traditional lenders, compared to fintech lenders, have a lower value for minority-owned businesses.

It is important to distinguish between these explanations because they have different policy implications for racial disparities in small business lending. The first explanation does not imply racial disparities in the lending market. In contrast, the second and third explanations call for greater attention to equitable credit access for small businesses owners, either in terms of alleviating the negative effect of lending relationships or reducing barriers in the lending procedure.

Our empirical analyses focus on PPP recipients in the *Food Services and Drinking Places* sector for which we can find a Yelp listing.[6] While restaurants only account for 4.40% of PPP loans, they offer several critical advantages for our study. First, it allows us to address the limitations of the PPP loan-level data, namely race and ethnicity data for borrowers is missing for almost 80% of the sample. We build a proxy for minority-owned businesses based on the food type from yelp.com.[7] In addition, we obtain data on customer ratings and use it as a proxy for operational performance. Second, in essence, all restaurants are eligible for the PPP and therefore there is no variation resulting from regulation.[8] Third, restaurants are among the most Covid-vulnerable sectors (Fairlie, 2020; Buffington et. al., 2021; Fairlie and Fossen, 2021b)[9], which provides strong participation incentives for borrowers. To identify fintech lenders, we mainly rely on the *FinTech Company List* published by the SBA, with manual checks of all non-banks.

Importantly, while we view the nationwide geographic scope and direct measurement of minority ownership on a firm-by-firm basis as strengths of our data construction, we acknowledge

[6] To have a comparable sample, we focus on yelp listings of restaurants. Others are gyms, nail bars, hotels, etc.
[7] Overall, as we present in detail, our racial group measures have reasonable accuracy when compared with the racial and ethnic information reported in the PPP data for the 20% of the sample of non-missing values.
[8] For most industries, the eligibility requirement is either meeting the SBA size standards for small businesses or less than 500 employees. For the industries with a NAICS code that begins with 72 (Accommodations and Food Services), a business is eligible for the PPP as long as the number of employees is fewer than 500 at each location.
[9] Other papers with the same findings or classifications include Alekseev et. al. (2021), Balyuk, Prabhala, and Puri (2020), Berger et. al. (2021), and Fazio et. al. (2021).

the incompleteness of the sample and the non-100% accuracy of the minority measurement.[10] By focusing on a subsample of PPP loans, our analyses aim to provide evidence of racial barriers in small business lending and the role of fintech lenders in alleviating them rather than assessing the efficacy of the PPP.

In the empirical analyses, we do not find consistent evidence on the first channel. We do find evidence that borrowers with higher ratings are more likely to use fintech lenders. However, the overall difference in ratings is lower for minority-owned businesses. This suggests that minority-owned businesses are less likely to use fintech lenders. Therefore, the higher popularity of fintech lenders among minority-owned businesses is unlikely to be attributed to a performance difference between minority and non-minority-owned businesses.

Instead, we find evidence supporting the second and third channels. Regarding the second channel, we find two pieces of evidence that, if combined, can lead to higher usage of fintech lenders among minority-owned businesses. First, we find that among the 2020 PPP recipients, minority-owned businesses are less likely to have lending relationships, and if they do, it is less intensive. Interestingly, racial disparities in lending relationships no longer exist among the 2021 PPP recipients. Second, our evidence shows that borrowers with no or few lending relationships are more likely to gain a PPP loan through fintech lenders.

Our findings also support the third channel. We document that the difference between minority- and non-minority-owned restaurants in customer ratings is more negative for fintech lenders. According to our model, this suggests that fintech lenders are preferred over traditional lenders for minority borrowers.[11] The reasoning behind this is that if fintech lenders, compared with traditional lenders, have a higher value for minority borrowers, the bar to be matched fintech lenders is lower, and thus we observe a lower rating level. In other words, our results suggest that minority-owned restaurants face lower barriers when using fintech lenders.

The results are consistent when restricting to a matched sample using business locations, food price range, and other characteristics as matching covariates. Furthermore, the results are robust when controlling for city × month fixed effects. Moreover, the magnitude of the difference in

[10] Our minority measure is most accurate for Asian-owned restaurants and all the results in 2020 are statistically significant at 1% for Asian-owned restaurants as well.

[11] We would not observe a more negative difference between minority- and non-minority-owned restaurants in ratings if more minority-owned small businesses use fintech lenders only due to the lack of previous lending relationships.

ratings can be used as a proxy for the level of racial barriers. Comparing the results for the 2020 and 2021 waves, we also observe a reduction in racial barriers in 2021.

When exploring heterogeneity among lenders, we find that the four largest banks in our sample, JPMorgan, Bank of America, Wells Fargo, and U.S. Bank, do not have a large minority-non-minority rating gap. The rating gap is more pronounced for relatively small big banks, Truist, PNC, and TD Bank, implying that smaller banks have higher racial barriers in the lending process. Furthermore, we investigate sources of racial barriers by exploring factors affecting the level of barriers. We find that the difference between fintech and traditional lenders in the minority-non-minority rating gap is smaller if borrowers have higher levels of business capital, proxied by the monthly number of ratings. For instance, for Asian recipients in 2020, one standard deviation increase in business capital reduces the minority-non-minority rating gap in the benchmark case by 106.69%. Business capital can be seen as soft assets that can mitigate racial barriers in the lending procedure. In addition, we find evidence that the difference in the minority-non-minority rating gap is smaller for more geographically focused lenders. Existing literature suggests that geographical distance is important in the acquisition and use of soft information (Agarwal and Hauswald, 2010), which can be another way to alleviate racial barriers.

We rule out several non-technology-related features of fintech lenders by studying other lender classifications. We do not find a similar pattern in lender usage and rating gaps for first-time banks (banks that did not previously participate in SBA 7(a) or 504 programs), community development financial institutions and corporations, credit unions, non-federally insured lenders, or savings & loan associations. We also rule out the possibility that minority-owned businesses are more likely to choose fintech lenders because of quicker approval. We find that, if anything, minority-owned businesses who applied through fintech lenders in 2020 waited longer to have a loan approved. Moreover, our results on the minority-non-minority rating gap are robust when controlling for approval date fixed effects, meaning that the racial gap does not come from a difference in loans approved earlier or later.

Overall, our findings suggest that racial barriers and blind spots exist in the traditional small business lending market. In the PPP program, minority-owned businesses are more likely to use fintech lenders. More importantly, we show that this effect cannot be simply explained by a performance difference between minority- and non-minority-owned businesses. There are deep-rooted racial disparities in terms of who has lending relationships, benefits from a lending process with fewer human-to-human contacts, and the value of lending relationships. On the bright side, consistent with the existing literature (Chernenko and Scharfstein, 2021; Fairlie and Fossen, 2021c), our evidence suggests that the racial gap is largely reduced in 2021, potentially due to the efforts of the Biden Administration.

There is a large body of literature on the PPP program.[12] In particular, several papers look at racial disparities in the program. Studies using the early release of the PPP loan-level dataset conduct county/zip code-level analysis (Fairlie and Fossen, 2021a; Erel and Liebersohn (2020); Wang and Zhang, 2020) or use the subsample with race and ethnicity information (Atkins, Cook, and Seamans, 2021). Two contemporaneous papers, Chernenko and Scharfstein (2021) and Howell et. al. (2021), like our paper, link the PPP dataset with other data sources to create a firm-level minority measure that allows for a richer set of findings.[13]

Our paper contributes to the literature on racial disparities in the small business credit market in several ways. First, we provide novel evidence to the scant literature on this important topic. Using a different sample and a different research design, our evidence is largely consistent with the contemporaneous papers and provides further support for the existence of racial disparities in the PPP. Second, we look at racial disparities through the lens of real-economy performance measures, which, to the best of our knowledge, is not investigated in other papers. From a societal view, a racial gap in terms of operational performance is an important angle through which to understand racial disparities in financial inclusion. Third, our evidence highlights an under-investigated but important type of racial disparities on the *borrower* side: barriers to reaching out to the same lender can be higher for minority borrowers. The existing literature focuses on the *lender* side and studies whether an anonymized lending procedure can reduce taste-based racial discrimination. Our paper shows another benefit of fintech lenders on achieving a more equitable

[12] See Berger and Demirgüç-Kunt (2021) for an early survey. Examples include Bartik et. al. (2020) and Granja et. al. (2020) on accessing the allocation, Autor et. al. (2020) on sustaining employment, Balyuk, Prabhala, and Puri (2020) and Cororaton and Rosen (2020) on reputational and disruption costs of receiving PPP funds, Duchin et. al. (2021) on favoritism of lending relationships, Humphries, Neilson, and Ulyssea (2020) on information frictions in the loan application procedure, Bartlett and Morse (forthcoming), Berger et. al. (2021), Denes, Lagaras and Tsoutsoura (2021) on real effects of the program, Berger, Karakaplan, and Roman (2021) and Duchin and Hackney (forthcoming) on political influence on the fund allocation.

[13] Chernenko and Scharfstein (2021) use restaurant registry data in the state of Florida, which has a high degree of accuracy. Our dataset covers all states and provides information on restaurant operational performance both before and during the Covid-19 crisis. Acknowledging the richness of data in Howell et. al. (2021) that relies on several proprietary datasets, our study provides sufficient economic insights using publicly available sources.

credit market. A more automatic lending process lowers the level of barriers for minority borrowers.

Our paper is also related to the nascent literature on fintech lending, particularly on the financial inclusion role of fintech lenders (Jagtiani and Lemieux, 2018; Mills and McCarthy, 2016), the relationship with traditional lenders in small business lending (Cumming et. al., 2019; Gopal and Schnabl, 2020; Beaumont, Tang, and Vansteenbergh, 2021), borrower side factors affecting fintech usage such as misreporting (Griffin, Kruger and Mahajan, 2021) and trust in the banking system (Yang, 2021), and racial discrimination in the lending procedure (Bartlett et. al., 2021; Fuster et. al., forthcoming; D'Acunto et. al., 2020). Our paper adds to the literature by showing that one role of fintech lenders on achieving a more equitable lending market is to provide credit to minority borrowers who are facing higher barriers to accessing traditional lenders.

The paper proceeds as follows. Section 2 presents a simple matching game model. Section 3 describes the data sources, the sample, and provides summary statistics. Section 4 provides evidence on the existence of racial disparities in borrower-lender matching. Section 5 shows the evidence on different channels generating racial disparities. Section 6 discusses alternative explanations. Section 7 concludes.

2. A Simple Model of The Borrower-Lender Matching Game

In this section, we develop a simple transferable utility matching game model (Azevedo and Hatfield 2018) to illustrate the matching process between borrowers and lenders in the PPP program. We present the basic model setup and the main results here. Further details on the assumptions, formal mathematical presentations and detailed deviations, and discussions can be found in the Online Appendix D.

Model Setup. There are a group of minority borrowers with a mass of M^m and a group of non-minority borrowers with a mass of M^n whose ratings follow the normal distribution $\gamma_i^m \sim N(\mu^m, \sigma^m)$, and $\gamma_i^n \sim N(\mu^n, \sigma^n)$ respectively.[14] There are a group of fintech lenders with a mass of M^f and a group of banks with a mass of M^b.

[14] Empirical patterns in Figure 2 support a normal distribution of ratings.

Payoff Function. The payoff function of a match between the borrower *i* and the lender *j*, $p_{i,j}(\gamma_i, \theta_{i,j})$, depends on the borrower's rating level γ_i and a lender-borrower dependent factor $\theta_{i,j}$, such as the borrower's preference for technology and the value of previous lending relationships between the borrower and the lender. $\theta_{i,j}$ is racial-neutral when we study the scenario with no taste-based discriminations. We study the equilibrium under taste-based discriminations using $\theta_{i,j} = \theta_{i,j}^m$ for minorities and $\theta_{i,j} = \theta_{i,j}^n$ for non-minorities. For simplification purposes, we assume that the payoff function is increasing in the borrower's rating γ_i and is of a linear functional form $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i + \theta_{i,j}$.

Matching Game. Without loss of generality, we study a 1-lender-m-borrower matching game.[15] The borrower *i* chooses a lender to apply to with an offered transferred utility (price). If the lender *j* accepts the application from the borrower *i*, a match (*i*,*j*) happens and the lender gains the transferred utility and the borrower gains the total payoff $p_{i,j}\left(\gamma_i, \theta_{i,j}\right)$ minus the transferred utility. If the lender *j* rejects the application from the borrower *i*, no match between the borrower *i* and the lender *j* happens and no total payoff is generated. The borrower *i* may apply to another lender or renegotiate the offered transferred utility. If no lender is willing to accept the borrower for any transferred utility that leaves a non-negative payoff to the borrower, the borrower is unmatched.

Equilibrium. In a competitive equilibrium, incentive compatibility means any deviation from either the borrower side or the lender side cannot achieve a higher payoff. The prices (transferred utilities) clear the market such that

$$p_{i,j}\left(\gamma_i, \theta_{i,j}\right) \geq p_{i,j'}\left(\gamma_i, \theta_{i,j'}\right) \; for\; j' \neq j \text{ and } p_{i,j}\left(\gamma_i, \theta_{i,j}\right) \geq p_{i',j}\left(\gamma_{i'}, \theta_{i',j}\right) \; for\; i' \in I \backslash I_j^* \quad (1)$$

Where *I* is the entire borrower set, and I_j^* is the optimal choice set of lender *j*.

In the following paragraphs, we discuss three scenarios. In the first scenario, the payoff function only depends on the rating level of the borrower. In the second scenario, the payoff function depends on the rating level of the borrower as well as a race-neutral lender-borrower

[15] In the PPP program, observations where a borrower is granted multiple loans are few. In our sample construction, fewer than 2% of the restaurants appeared to be associated with multiple loans. We exclude those observations from our analysis sample.

factor $\theta_{i,j}$. In the third scenario, the payoff function depends on the rating level of the borrower and a race-biased lender-borrower factor $\theta_{i,j}^{m/n}$.

Benchmark. In the benchmark case where the payoff function only depends on the borrower's rating level $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i$. We have a unique symmetric equilibrium where fintech lenders and banks are matched with borrowers whose ratings are above the same threshold $\underline{\gamma}$ for both the minority and non-minority groups. $\underline{\gamma}$ is determined by

$$\delta M^m \int_{\underline{\gamma}}^{\infty} f(x, \mu^m, \sigma^m) dx + \delta M^n \int_{\underline{\gamma}}^{\infty} f(x, \mu^n, \sigma^n) dx = M^f$$

$$(1-\delta) M^m \int_{\underline{\gamma}}^{\infty} f(x, \mu^m, \sigma^m) dx + (1-\delta) M^n \int_{\underline{\gamma}}^{\infty} f(x, \mu^n, \sigma^n) dx = M^b$$

Where $f(\mu^m, \sigma^m)$ and $f(\mu^n, \sigma^n)$ are the density functions of the rating distribution for the minority and non-minority borrowers respectively. Figure 2 plots the rating distribution for different racial groups and it follows a normal distribution truncated at the maximum of rating stars.

[INSERT FIGURE 2 AROUND HERE]

Race-Neutral Borrower-Lender-Specific Payoff. The payoff function depends on the rating of the borrower as well as a *race-neutral* borrower-lender-specific factor $\theta_{i,j}$. We discuss two reasons why the payoff function can be borrower-lender specific.

First, we consider the tech-preference case that higher-rated borrowers have a higher preference for technology and therefore have a higher payoff when matched with fintech lenders than with banks.[16] Notably, however, we assume that minority and non-minority borrowers of the same rating level have the same additional preference for fintech lenders to banks. In this case, we still have a race-neutral equilibrium in terms of rating levels of minority and non-minority borrowers matched with fintech lenders and with banks. Unlike the benchmark case, the average rating of borrowers matched with fintech lenders is higher than banks due to the self-selection of higher-rated borrowers into fintech lenders.

[16] We have similar results if assuming lower-rated borrowers have a higher preference for technology. Detailed discussions in Online Appendix D. Since our empirical pattern is consistent with that higher-rated borrowers self-select into fintech lenders, we make the assumption in the increasing direction in the main text.

Second, we discuss the lending-relationship case where the payoff functions are different for borrower-bank matches with and without previous lending relationships but in a race-neutral way. Previous lending relationships play a crucial role in the PPP program (Li and Strahan forthcoming; Duchin et. al. 2021). For example, on the lender side, helping existing customers to survive the crisis may alleviate the debt overhang problem (Amiram and Rabetti 2020). On the borrower side, the existing profile of the borrower can make it easier to navigate the application process.

In this case, we also have a race-neutral equilibrium in terms of rating levels. Because of the additional utility from lending relationships, the marginal borrower with lending relationships is of a lower rating level than the marginal borrower without lending relationships. This crowds out some of the higher-rated borrowers without lending relationships from banks to fintech lenders, which results in a higher average rating level for borrowers matched with fintech lenders than with banks.

When the payoff function is race-neutral, the phenomenon that minority borrowers being more likely to be matched with fintech lenders can occur due to two channels. First, it can be generated through the channel of higher average ratings for minority borrowers, combined with the self-selection effect of higher-rated borrowers or the crowding-out effect by lower-rated borrowers having bank lending relationships. Second, it can also be attributed to a smaller mass of minority borrowers having lending relationships than non-minority borrowers.

Race-Dependent Borrower-Lender-Specific Payoff. The payoff function depends on the rating of the borrower as well as a *race-biased* borrower-lender-specific factor $\theta_{i,j}^{m/n}$. There can be several reasons for such a difference in the payoff for fintech lenders versus banks between the minority and non-minority borrowers. For example, a less bureaucratic process and fewer human contacts in a fintech loan application may benefit minority borrowers who may have language and culture barriers. It is also possible that minority borrowers might have had previous negative experiences with banks and therefore have a higher expectation from new technology-oriented lenders. On the lender side, it is much less costly for fintech lenders to reach any region, including those that are covered less by traditional financial institutions but with a larger minority population.

In the tech-preference case, the additional utility gain from matching with fintech lenders is race-biased. As in the race-neutral case, the additional utility from technology results in a higher matching threshold in terms of rating levels for fintech lenders than for banks. Unlike the race-neutral case, the equilibrium is race-asymmetric in terms of the matching thresholds in ratings for fintech lenders. For the group of borrowers that have a higher value for fintech lenders, they are willing to transfer a higher share of the total payoff to fintech lenders. This results in a smaller matching threshold of fintech lenders for that group of borrowers. Proposition 1 presents this result.

Proposition 1

In the race-biased tech-preference case, the matching thresholds for the matches of minority-fintech, non-minority-fintech, minority-bank, and non-minority-bank in equilibrium satisfy,

$$\underline{\gamma_{mf}} = \frac{\theta^n}{\theta^m}\underline{\gamma_{nf}}$$

$$\underline{\gamma_{mb}} = \underline{\gamma_{nb}}$$

■

Proof in the Appendix.

Proposition 1 implies that when minority borrowers have a higher preference for technology than non-minority borrowers with the same rating level ($\theta^m > \theta^n$), the matching threshold with fintech lenders is lower for minority borrowers than for non-minority borrowers ($\underline{\gamma_{mf}} < \underline{\gamma_{nf}}$). This has two important implications. First, a lower matching threshold for minority-fintech matches results in a relatively larger share of minority borrowers than non-minority borrowers using fintech lenders even without a difference in the underlying rating distribution. Second, a lower matching threshold for minority-fintech matches implies a more negative minority-non-minority rating gap of the marginal borrower for fintech lenders, which can be translated into a more negative minority-non-minority rating gap in the expected mean of matched pairs for fintech lenders. Corollary 1 presents this result.

Corollary 1

The minority-non-minority rating gap in the matching thresholds is more *negative* (*positive*) for fintech lenders when minority borrowers compared with non-minority borrowers have a *higher* (*lower*) value of matches with fintech lenders.

$$\left(\underline{\gamma_{mf}} - \underline{\gamma_{nf}}\right) - \left(\underline{\gamma_{mb}} - \underline{\gamma_{nb}}\right) \lesseqgtr 0 \; if \; \theta^m \gtreqless \theta^n$$

Suppose that the underlying distribution is the same for minority and non-minority borrowers, i.e., $\mu^m = \mu^n = \mu$ and $\sigma^m = \sigma^n = \sigma$, then the minority-non-minority rating gap between fintech lenders and banks in the conditional expectation of the rating levels equals $\sigma\left(G\left(\frac{\underline{\gamma}_{mf}-\mu}{\sigma}\right) - G\left(\frac{\underline{\gamma}_{nf}-\mu}{\sigma}\right)\right)$, where $G(x) = \frac{\varphi(x)}{\Phi(-x)} + \frac{\varphi(x)-\varphi(\tilde{\gamma})}{\Phi(x)-\Phi(\tilde{\gamma})}$, with $\tilde{\gamma} = \frac{\underline{\gamma}_{mb}-\mu}{\sigma}$ and $\varphi(\cdot)$ and $\Phi(\cdot)$ as the density and cumulative distribution functions of the standard normal distribution respectively.

■

Proof in the Appendix.

In the lending-relationship case, the payoff function contains an additional utility gain for borrower-lender matches with previous lending relationships which is race-biased. Mirroring the tech-preference case, the equilibrium is race-asymmetric in matching thresholds for borrowers with previous lending relationships. This is because the racial group of borrowers with a higher value of lending relationships are willing to transfer a higher share of the total payoff to lenders. As a result, the matching threshold in equilibrium is smaller for that racial group. For borrowers without lending relationships, the matching threshold in equilibrium is race-independent because their outside option is the same. Similar to the tech-preference case, the race-asymmetric matching thresholds further translate into a racial gap in the shares as well as the average rating levels of borrowers that are matched with fintech lenders and banks.

In summary, our model shows that the phenomenon that a higher usage rate of fintech lenders among minority borrowers can be generated through several distinct channels. On the one hand, it can exist in a race-neutral equilibrium through two channels. First, the combination of higher- (lower-) rated borrowers being more likely to be matched with fintech lenders, whether due to the self-selection or the crowding-out effects, and a higher- (lower-) average rating for minority-owned businesses can be one channel. Second, if fewer minority borrowers have lending relationships with banks, we also observe more fintech usage among minority borrowers than among non-minority borrowers. On the other hand, racial bias can also lead to the difference in the usage of fintech and non-fintech lenders. In our model, we show that if minority borrowers have a higher preference for technology-based lending process or if the value of lending relationships is higher for non-minority borrowers, a larger share of minority borrowers are matched with fintech lenders in equilibrium. Notably, we also observe a difference in the minority-non-minority rating gap between fintech and non-fintech lenders in the race-biased case. We shall test the different channels in the empirical analysis followed.

3. Data and Summary Statistics

3.1. Data sources

Our analysis relies mainly on a linked database of loan-level information on restaurants in the Paycheck Protection Program (PPP) and the full history of customer ratings downloaded from Yelp.com. For the PPP dataset, we use the loan-level data release on March 2, 2021 (through sba.gov, FOIA), which is the most detailed and comprehensive version of loans of all sizes. The entire PPP dataset contains around 6.46 million loans processed by 5,593 lenders, among which around 0.37 million loans (5.77%) are for businesses in the *Food Services and Drinking Places* sector (NAICS code 722). The key information we use from the PPP data includes the business name, address, state, zip code, industry, business entity type, reported employment size, and franchise name for borrowers; and the formal organization name, address, city, state, and zip code for lenders. We restrict our loan sample to only first draws in order to better capture the matching between borrowers and lenders. The completeness of the 2021-March release of the PPP data enables us to address questions that have not been answered in previous studies,[17] and is crucial for our study because minority-led businesses tend to be smaller (Fairlie and Robb 2008; U.S. Census Bureau 2016; Tareque et. al. 2021) and received a smaller loan (Atkins, Cook, and Seamans 2021; Fairlie and Fossen 2021a).

First and foremost, to carry out our analysis we need to distinguish between traditional and fintech lenders, for which we mainly rely on the *FinTech Company List* published on the SBA official website (sba.gov). We supplement the official *FinTech Company List* with information from the SBA state subsidiaries' websites and major news sources.[18] We identify 15 fintech

[17] Other papers studying the Paycheck Protection Program (Erel and Liebersohn 2020; Granja et. al. 2020; Li and Strahan forthcoming) use the early release of the PPP data that contains borrower names only for loans *above* $150,000. The full release used in our paper contains borrower-level identifiable information for loans both above and below $150,000, which enables us to link with Yelp rating data for the full sample.

[18] To cross validate our consolidated fintech company list, we manually go through the entire sample of non-bank lenders and do not identify any lenders that are clearly a fintech company but not in our fintech lender list.

lenders and the full list is in Table A2 in the Appendix.[19] Examples of fintech lenders in our list are Kabbage, Square, and Paypal. Appendix-Table A2 also reports the percentage of loans that are included in our final sample linked with Yelp ratings, which indicates that our linked sample is evenly distributed across each fintech lender. We present the comparison between our sample and the Erel and Liebersohn (2020) sample in the Online Appendix B-Table B1, which further confirms the reliability of our classification. Details on the construction of the sample of fintech lenders are stated in the Online Appendix C1.

One thing to notice about our classification method is that we do not classify all non-banks as fintech lenders because one crucial feature of SBA lending programs is the participation of many traditional non-bank lenders, such as CRF Small Business Loan Company, LLC and Hana Small Business Lending, Inc., as means to facilitate the funding needs of less bank-connected small businesses. Regarding the lending technology, these non-banks are similar to banks and are different from fintech companies. Other papers on small business lending (Gopal and Schnabl 2020) and the mortgage credit market (Buchak et. al. 2018; Fuster et. al. 2019) also make the distinction between fintech companies and other non-banks.

Second, we need to identify minority-owned businesses among PPP loan recipients for a representative sample. One limitation of the PPP loan-level data is that the information on the race and ethnicity of loan recipients is missing for almost 80% of the sample.[20] Because there might be a selection bias in the sample that has the demographic information, we do not rely on the demographic information in the original PPP loan-level dataset. To address this challenge, we restrict to a sample of restaurants among the PPP recipients for which we find a match on yelp.com. Then we use the food type information on yelp.com as a proxy for the race and ethnicity information of the restaurant owners. We classify restaurants into four groups: African American, Asian (including Pacific Islander), Hispanic, and White. The detailed classification list is available upon request.[21] We cross validate our measure of minority-owned business by comparing the Yelp racial group variables and the PPP racial group variables and results are reported in Appendix

[19] The 2020-March data release includes both the originating and the servicing lenders, and we classify the pair of lenders as a fintech lender when either of them is in our consolidated list of fintech lenders.

[20] As the application did not ask for demographic information of the business owners, the race and ethnicity information is self-reported by lenders and concentrated among a few lenders (Fairlie and Fossen (2021a)). Coverage of the race and ethnicity information increases in later periods when the SBA began to pay more attention to the racial gap in the loan distribution.

[21] Some examples are African, Somali, and Soul Food as African American; Asian Fusion, Japanese, Chinese, and Pakistani as Asian; Acai Bowls, Caribbean, and Mexican as Hispanic.

Table A3. While we occasionally mismeasure the racial groups, overall, our race proxy based on Yelp information is highly and positively correlated with the true racial category and has a reasonable level of accuracy.[22]

The concurrent literature addresses the data incompleteness of demographic information by conducting zip-code/county level analysis (Erel and Liebersohn 2020; Fairlie and Fossen 2021a), restricting to the subset of PPP recipients with demographic information (Atkins, Cook, and Seamans 2021), estimating the racial group based on borrower name and location (Howell et. al. 2020). One distinct paper is Chernenko and Scharfstein (2021) that links the PPP data with restaurant licenses and voter registrations in Florida and identifies the race and ethnicity group of restaurant owners using the registration information. As independent research, we also link the PPP data to other data sources to identify minority-owned businesses. Unlike Chernenko and Scharfstein (2021), our sample covers all 50 states and Washington, D.C. The wide geographic scope of our sample and the fact that we do not rely on location information when building the proxy allows us to investigate racial disparities across different locations as well as in the same location.

Third, we use the customer ratings from yelp.com to gauge the the minority-non-minority gap between fintech and non-fintech borrowers. Yelp ratings are used as a proxy for operational performance (Bernstein and Sheen 2016) and shown to be related to revenue increase (Luca 2016).[23] The fact that Yelp ratings have a uniform range from 0 to 5 provides a comparable way to investigate disparities in the valuation across lenders for borrowers of different racial groups. We collect the full history of the ratings and construct a restaurant-month panel by taking the average of ratings in each month for each restaurant.

Using a panel of the ratings has the benefits of the possibility of controlling for time trends in ratings by including monthly fixed effects. In addition, it allows us to look at the operational

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[22] Panel A of Appendix Table A3 shows that around 80.1%, 51.9%, and 89.6% of the African, Hispanic, and Asian restaurants based on the Yelp information have an owner of the same racial group according to the PPP information, respectively. Panel B reports that around 61.5%, 16.2%, and 62.0% of the African Americans, Asians, and Hispanics own a restaurant of the corresponding type. The main false negative comes from African Americans owning a restaurant that was thought to be White. Panel C reports the pairwise correlation between the PPP and Yelp racial group measures, which shows strong and positive correlations, 0.35, 0.52, and 0.68 for African American, Asian, and Hispanic respectively, and statistically significant at the 1% level.

[23] There is recent literature discussing the effectiveness of customer ratings (Mayzlin, Dover and Chevalier (2014)), and using the Yelp ratings as a measure of restaurant sales (Anderson and Magruder (2012)) and visits (Davis et. al. (2019)), and investigating the informativeness of customer ratings in residential home services (Farronato et. al. (2020)), physician choice (Xu, Armony and Ghose (2021)), and books on Amazon (Reimers and Waldfogel (2021)).

performance both for the period before the Covid-19 crisis and the period during the Covid-19 crisis. It is important to distinguish between the operational performance before and during the pandemic for our study. Restaurants may differ in the change of operational performance due to the Covid-19 crisis, which may result in variation in the degree of difficulties when seeking the PPP loan from traditional and fintech lenders.

Lastly, we merge in other datasets to enrich the scope of our analysis, including other restaurant-level information from yelp.com, 7(a) and 504 program loan-level data from 1990 to 2019, and HUD USPS zip code crosswalk files. In addition, we classify lenders into banks, Certified Community Development Financial Institutions (CDFIs) loan funds/Certified Development Companies (CDCs), and other non-banks. We then match the PPP lenders in our final linked restaurant sample with financial institutions on the Federal Financial Institutions Examination Council (FFIEC) list.[24] Taking advantage of the lender information from FFIEC, we further determine whether the lender is a federally insured institution, a credit union, or a savings & loan association. Details on the lender classification and steps to match with FFIEC are in Online Appendix C2. Details on variable definitions and data sources can be found in Table A1 in the Appendix.

3.2. Sample design

We construct a linked database by matching the borrowers in the PPP dataset to the restaurants on yelp.com. The PPP-Yelp linked dataset offers several advantages. First, it provides information on detailed borrower-level characteristics and a proxy for minority-owned businesses for a representative sample. Second, essentially all restaurants were eligible for PPP while the standard is higher in other industries. Details in the appendix. This rules out the possibility that our results are driven by sample selection bias due to eligibility.[25] Third, the restaurant industry is among the most Covid-19 vulnerable industries. Studying the restaurant borrowers can shed light on how Covid-19 sensitive industries perform during the crisis. Overall, we believe that our linked datasets give us a unique opportunity to study the small business loan market, especially for what drives minority borrowers to use fintech lenders.

[24] We restrict to lenders who lent over 100 loans in the entire PPP program, excluding CDFI, CDC, and non-bank fintech lenders.
[25] For example, if the eligibility is size-based, we would have a different sample of the minority-owned businesses than non-minority-owned businesses that are eligible for the PPP as the minority-owned businesses tend to be smaller.

We use both code-based algorithms and manual corrections for the matching procedure and employ strict matching criteria that only to include the matches between the PPP recipient and the Yelp-listed restaurant that have meaningful connections in terms of both the name and address. Details on the linking procedure are described in the Online Appendix C3. 104,293 loans are matched to a meaningful link on yelp.com, which account for 28.01% of the whole PPP sample in the *Food Services and Drinking Places* sector. The matching rate is reasonable given that our matching criteria are strict. For the empirical analysis, we focus on the period from April 2018 to March 2021 and limit the sample to restaurants that have at least one rating record since April 2018.[26] Online Appendix C3 also provides a comparison between the linked and unlinked samples which shows a high similarity between two.

3.3. Summary statistics

We mainly use two datasets: one cross-sectional dataset that consolidates the various data sources described above and one restaurant-level panel dataset on historical customer ratings. Our final cross-sectional dataset consists of 98,825 restaurant borrowers in the PPP that are active in business from April 2018 to March 2021.[27] The observation level is a restaurant-lender-loan triplet. The loan and lender characteristics are observed at the PPP loan origination time; the restaurant characteristics are from yelp.com and are observed at the time of data collection (March to July, 2021). The restaurant-level panel dataset provides the monthly average of rating stars for the 98,825 restaurants in our sample from April 2018 to March 2021.

[INSERT TABLE 1 AROUND HERE]

Table 1.1 shows the summary statistics of key variables in the cross-sectional dataset for the borrowers in the 2020 (Panel A) and 2021 (Panel B) waves. We report the results for both the full and the matched samples. The matched sample is constructed by matching minority borrowers with non-minority borrowers in the same state, business type group (aggregated), food price range, and of a similar size with a difference of at most five employees. By employing the matched sample

[26] This deletes about 2.88% of the observations in the linked sample.
[27] We further exclude a total of less than 2% of the observations of non-restaurants, restaurants located in Puerto Rico, Northern Mariana Islands, Guam, and U.S. Virgin Islands, and where one Yelp link is matched to multiple loans.

methodology, we take into account the possibility that the above-described matching covariates may affect our results non-linearly.

The recipients in the 2021 wave appear to be different from the recipients in the 2020 wave in our sample. 32% of the 2020 and 38% of the 2021 recipients are minorities; 12% in 2020 and 6% in 2021 are in franchise chains; 9% in 2020 and 17% in 2021 use fintech lenders; 3% in 2020 and 2% in 2021 have lending relationships. The average borrower in 2020 (2021) has 18.62 (9.39) employees, waits 26.87 (41.12) days for loan approval, and has a total number of 52.08 (33.01) customer reviews during the period from April 2018 to March 2021. Overall, the 2021 wave tends to contain a larger part of financially disadvantaged borrowers than the 2020 sample.

When comparing the full and matched samples, in 2020, the minority and racial group variables are close, with a slightly higher share of Asian-owned restaurants in the matched sample. In other dimensions, restaurants in the matched sample have fewer employees, less business capital, more days to gain an approved loan, are less likely to be franchised, more likely to use fintech lenders, have similar lending relationships, and are matched with lenders with a larger geographic lending scope. Similar patterns hold for the 2021 wave, except that approval days are slightly lower for the matched sample in 2021. These differences in the full and matched samples are consistent with the minority-owned businesses being in a disadvantaged location and business status.

Table 1.2 shows the summary statistics of rating stars in the panel dataset for the borrowers in the 2020 (Panel A) and 2021 (Panel B) waves. The ratings are quite similar for the full and matched sample. However, the average rating is higher during the Covid-19 period (3.92 for the 2020 recipients and 4.06 for the 2021 recipients) than (3.84 for the 2020 recipients and 3.95 for the 2021 recipients). These numbers also mean that the 2021 recipients have higher ratings than the 2020 recipients on average. The differences between the 2020 and 2021 recipients are worth noticing as the latter are more likely to be minority-owned, smaller but of higher ratings.

4. Existence of Racial Disparities

This section investigates whether there is a systematic difference in the usage rate of fintech versus traditional lenders in the PPP program for minority- and non-minority-owned restaurants.

4.1. Fintech lenders in the PPP program

In this subsection, we illustrates the usage of fintech and non-fintech lenders for minority- and non-minority-owned restaurants.

[INSERT FIGURE 3 AROUND HERE]

Figure 3 shows the daily dollar value of loans processed by fintech lenders (Panel (a)) and non-fintech lenders (Panel (b)) for minority- and non-minority-owned restaurants. In the first tranche, major fintech lenders were only allowed to participate in the PPP program in 2020 one week after the initial launch.[28] Before the entry of major fintech lenders on April 10, 2020, there is an enormous gap between the dollar value of loans disbursed to minority- and non-minority-owned businesses. For example, on the first day, the dollar value of loans disbursed by traditional lenders to the minority-owned businesses is only 7.54% of the dollar value disbursed to the non-minority-owned businesses. In contrast, fintech lenders processed more than three million dollars of loans for minority borrowers on the first day of entry, about 35.96% of the dollar value fintech lenders disbursed to non-minority borrowers.

In the second tranche that started on April 27, 2020, traditional lenders covered a relatively larger share of minority-owned businesses than in the first tranche, consistent with findings using the early data release of the subsample of larger loans (Fairlie and Fossen 2021a). However, the gap between fintech and traditional lenders is still prominent, with a 53.38% minority-non-minority ratio for traditional lenders and a 75.27% minority-non-minority ratio for fintech lenders as measured by dollar value. Figures plotting the daily *number* of loans processed by fintech and traditional lenders show a similar pattern and are in the Online Appendix A Figure A1.

We further decompose the minority-owned businesses into African American-, Asian-, and Hispanic-owned businesses and plot the daily disbursed dollar value by fintech and non-fintech lenders in the Online Appendix A Figure A2. The patterns look analogical across the three racial groups, especially after the entry of major fintech lenders, suggesting that fintech lenders serve as a crucial channel of accessing PPP loan for all the three groups.

4.2. Geographic variation in fintech lending

[28] https://www.lendacademy.com/fintech-lenders-can-finally-apply-to-be-part-of-the-ppp/. Some fintech lenders participated in SBA 7(a) programs before 2020, and therefore were allowed to process PPP loans from the beginning. In our sample, fintech lenders that processed loans before April 10, 2020 are Celtic Bank Corporation, Cross River Bank, Readycap Lending, L.L.C., and Sunrise Banks, National Association.

In this subsection, we explore the geographic variation in fintech lending in the PPP program.

[INSERT FIGURE 4 AROUND HERE]

Figure 4 plots the state-level minority shares separately for fintech loans and non-fintech loans. Figures 4(a) and 4(b) plot the minority share for fintech loans and figures 4(c) and 4(d) for non-fintech loans in 2020 and 2021, respectively. The cross-state variation in the minority shares for non-fintech loans are moderate. In contrast, we observe a larger dispersion across states in minority shares for fintech loans. These results suggest that fintech and non-fintech lenders play a different role in providing credit to minority-owned businesses. All patterns are similar when we use the total *number* of loans to measure minority shares, as shown in Online Appendix A Figure A3.

4.3. Fintech lenders and minority borrowers

Next, we investigate whether minority-owned restaurants are more likely to use fintech lenders in the PPP program in a regression framework. We estimate the following specification:

$$I(Fintech)_{i,c} = \beta I(Minority\ Group)_i + \gamma X_i + \mu_c + \varepsilon_{i,c}$$

where the main dependent variable is a dummy variable equal to one if the restaurant owner *i* borrows from a fintech lender in the PPP program and 0 otherwise. The main independent variables, *African American*, *Asian*, and *Hispanic*, are dummy variables equal to one if the restaurant owner *i* is African Americans Asian, or Hispanic and 0 otherwise. The omitted category is other racial and ethnic groups, mainly composed of White-Americans.

To control for other borrower characteristics to the greatest extent possible given the available data, we include *Employment* for business size, *I(Franchise)* for whether the business is a franchised brand, *Business Type Dummies* for different company organizational formats such as Corporation, L.L.C., Sole Proprietorship, and Self-Employment (Details in Appendix-Table A1). We include city fixed effects (μ_c) to control for time-invariant variation in local economic exposure to the Covid-19 shock and pre-pandemic conditions that might affect the propensity to get a fintech loan. Standard errors are clustered at the city level.

[INSERT TABLE 2 AROUND HERE]

Table 2 columns (1) through (4) present the results on the 2020 wave. Column (1) shows that African American- and Asian-owned restaurants have an 8.00% and 7.43%, correspondingly, higher likelihood of using a fintech lender. However, for Hispanic borrowers, the difference in the likelihood of using fintech and traditional lenders is only 0.88%, which is small in terms of economic magnitude. Coefficients are statistically significant at the 1% level for all groups.

In column (2), we control for city fixed effects and compare the characteristics of business owners in the *same city* who borrow from different lenders. The coefficient before the *African American* dummy decreases to 4.99%, which is around 37.63% of the coefficient without city fixed effects. The coefficient before the *Asian* dummy also decreases and becomes 18.30% of the coefficient without city fixed effects. The coefficient before the *Hispanic* dummy is negligible and statistically insignificant when controlling for city fixed effects. The large reduction in the economic magnitude and statistical significance of the coefficients when controlling for city fixed effects suggests that the geographic variation across cities explains a large part of the higher likelihood of using fintech lenders by minority-owned businesses. Results are robust when using the matched sample and are presented in columns (3) and (4).

Columns (5) through (8) present the results of the 2021 wave. Like the 2020 wave, we observe that minority-owned businesses have a higher likelihood of using fintech lenders. The economic magnitude is even larger than for the 2020 wave. For example, column (5) shows that the coefficients before *African American*, *Asian*, and *Hispanic* dummies are 2.02, 1.36, and 5.63 times as large as the coefficients in the 2020 wave, respectively. In addition, cross-city variation also plays an even larger role in the 2021 wave. As shown in column (6), the coefficient before the *Asian* dummy decreases to 6.10%, the coefficient before the *African American* dummy becomes insignificant, and the coefficient before the *Hispanic* dummy decrease to 3.31%. These results suggest that the role of within-city variation in lender choices is reduced in the 2021 wave. Results are robust when using a matched sample, as reported in columns (7) and (8).

In Online Appendix Table B2, we do the same analysis but employ one dummy variable, *Minority*, that equals one if the restaurant *i* is a minority-owned restaurant and 0 otherwise. Results are consistent with the findings presented here.

In all specifications, *Employment Size* is negatively related to the propensity to use fintech lenders, which is consistent with the existing papers showing that banks prioritize larger customers (Balyuk, Prabhala, and Puri 2020; Humphries, Neilson, and Ulyssea 2020). Franchised restaurants also tend to be less likely to apply for a PPP loan through fintech lenders, which is as expected given that their parent companies have stronger relationships with banks.

Taken together, our evidence supports the argument that minority-owned businesses are more likely to use fintech lenders than traditional lenders. We find that this effect is the strongest for African Americans, followed by Asians and then for Hispanics. To a large extent, the higher likelihood of using fintech lenders by minority-owned businesses is attributed to regional variation, which tends to have historical roots such as “bank deserts” on the lender side (Erel and Liebersohn 2020; Wang and Zhang 2020) and language and business capital weakness on the borrower side. These historically rooted factors are hard to eliminate in a short period of time. Moreover, consistent with Chernenko and Scharfstein (2021) and Howell et. al. (2021), we still observe racial disparities after controlling for city fixed effects, suggesting culture- and attitude-based racial bias plays an important role in the outcome of PPP loan distribution.

Encouragingly, we do observe an improvement in terms of racial inequality in the loan distribution process in the 2021 wave. The economic magnitude of the likelihood of using fintech lenders is larger in the 2021 wave than in the 2020 wave, consistent with a learning effect within the minority communities in order to access the government fund. Moreover, the within-city variation also contributes to the racial disparity in fintech usage by a smaller degree in the 2021 wave, suggesting that the unequal access to PPP loans driven by racial bias is also likely to be reduced.

4.4. Minority-non-minority rating gap

We next explore the existence of racial bias through the lens of Yelp ratings. Motivated by our matching game model, we investigate whether minority-owned restaurants are more valued with fintech lenders than with non-fintech lenders based on the operational performance of restaurants.

[INSERT TABLE 3 AROUND HERE]

Table 3 regresses the Yelp ratings on the interaction term between the fintech lender indicator and the three minority racial group indicators respectively, which compares the minority-non-minority rating gap between fintech and non-fintech borrowers. Panel A presents the results for the 2020 wave, and Panel B for the 2021 wave. The dataset is a restaurant-month panel where the dependent variable is the monthly average of customer ratings for a given restaurant. The key independent variable is the interaction terms between the fintech indicator and the three racial group indicators. We also control for the indicators themselves as well as borrower characteristics, which are time-invariant variables. We account for within-restaurant correlation in errors by clustering all panel regressions by restaurants. In each panel, columns (1) through (4) report the results for the pre-Covid period from April 2018 to March 2020, and columns (5) through (8) for the during-Covid period from April 2020 to March 2021.

In the 2020 wave, Panel A columns (1) through (4) show that the coefficients before the interaction terms between the fintech lender indicator and the African-American indicator are insignificant when using ratings from the pre-Covid period. However, as shown in columns (5) through (8), when using ratings during-Covid, the coefficients before the interaction terms are negative and statistically significant at the level of 5%. For example, in column (5), the rating gap between African-American- and non-minority-owned restaurants is 0.25 stars (or 6.5% of the sample mean) more negative for the borrowers of fintech lenders than for the traditional lenders. The difference in the results using the pre- and during-Covid period suggests that the African-American-owned small businesses that were hit especially hard by the Covid-19 crisis (Fairlie 2020; Couch, Fairlie, and Xu 2020) experienced relatively more difficulties in getting a PPP loan from traditional lenders. For Asian-owned restaurants, we find a more negative minority-non-minority rating gap using both the pre- and during-Covid period. For example, in column (1), the rating gap between Asian- and non-minority-owned restaurants is 0.08 stars (or 2% of the sample mean) more negative for the borrowers of fintech lenders than for the traditional lenders. Results of the Hispanic-owned restaurants are insignificant. Results with and without city fixed effects are similar, suggesting that racial disparities exist both across and within cities. Results using the matched sample are robust.

We observe different results in the 2021 wave. The coefficients before the interaction terms between the fintech and racial group indicators for African-American- and Asian-owned restaurants become insignificant, yet for Hispanic-owned restaurants, we observe negative coefficients before the interaction terms when using ratings of the during-Covid period. For example, Panel B column (5) shows that the rating gap between Hispanic- and non-minority-owned restaurants is 0.18 stars (or 4.6% of the sample mean) more negative for those who use fintech lenders than for those who use traditional lenders. Results are robust with or without city fixed effects and when using the full or matched sample.

The difference in the rating gap between the 2020 and 2021 waves implies a shift in the segment of borrowers covered by fintech lenders as we look at the first-time loan recipients instead of the re-applications in both waves. One possible explanation is that Africans and Asians are more familiar with fintech lenders and start using them in the 2020 wave. As most of the African American and Asian borrowers in the blind zone of traditional lenders already participated in the PPP program in 2020, the additional part of the African and Asian borrowers in the 2021 wave via fintech lenders are similar to non-minority borrowers. Hispanics might have been less aware of fintech lending before. However, through the massive media coverage of fintech in PPP, and through the stories from other minority-owned businesses, a greater number of Hispanic borrowers neglected by traditional lenders applied for PPP loans via fintech lenders in 2021.

In Online Appendix Table B3, we do the same analysis but employ one dummy variable, *Minority*, that equals one if the restaurant *i* is a minority-owned restaurant and 0 otherwise. Results are consistent with the findings presented here. Table B4 presents the results where we run regressions on separable subsamples of fintech and non-fintech borrowers. We find that the minority-non-minority rating gap is positive, or less negative, for traditional lenders, which is consistent with traditional lenders having higher requirements for minority borrowers than non-minority borrowers, explicitly or implicitly through selection effects in matching.

Overall, we find that a smaller minority-non-minority rating gap for fintech users, suggesting that minority-owned businesses are less undervalued when matched with fintech lenders. Our evidence implies that non-minority-owned businesses can access the traditional credit market more easily. For minority-owned businesses with a similar rating level, they might have to turn to new technology-based lenders, such as fintech lenders.

4.5. Lender heterogeneity

We further explore heterogeneity among lenders by running the same regression specifications as in Table 3 but using a series of dummies, one for each lender. We focus on the four biggest fintech lenders: Cross River Bank, Kabbage, Square, and Paypal, and the seven largest banks: JPMorgan, Bank of America, Wells Fargo, U.S. Bank, Truist, PNC, and TD Bank. We set the threshold of big lenders where each lender covers at least 1% of the observations in our restaurant-month panel dataset of ratings.[29]

[INSERT FIGURE 6 AROUND HERE]

Figure 6 shows the results for the largest minority group in our sample: Asian-owned restaurants. Consistent with the pooled-lender regression results, the Asian-non-minority gap in ratings is negative for the 2020 wave for all fintech lenders compared with non-fintech lenders, except for that the rating gap is slightly positive for Cross River Bank using ratings during the Covid-19 period. Overall, smaller fintech lenders tend to have a more negative rating gap, indicating a larger financial inclusion role of smaller lenders for minority-owned businesses.

In contrast, smaller banks tend to display higher racial bias. For the largest three banks, JPMorgan, Bank of America, and Wells Fargo, the rating gap is either small or not significantly different from zero, suggesting that big banks provide credit to a similar group of minority- and non-minority-owned restaurants in terms of rating levels. For relatively "small" big banks, the rating gap is positive and large.

In 2021, there is no clear difference between fintech lenders and banks. This aligns with our pooled-lender regressions and implies an improvement in 2021 that fintech and non-fintech lenders provide credit to a similar segment of minority- and non-minority-owned businesses. This change may be the result of lenders' reaction to media pressure in reducing racial discrimination. It can also be attributed to the less demanding credit needs of borrowers so that the constraints for minority borrowers are relaxed.

Online Appendix Figure A4 and Figure A5 present plots for the African Americans and Hispanics, respectively, where the patterns are also consistent with our results of the pooled-lender regressions.

5. Sources of Racial Disparities

In this section, we investigate the sources of friction that contributes to racial disparities in fintech usage we observe in the PPP program.

[29] Cross River Bank, JPMorgan, Bank of America, and Wells Fargo each cover about 2.20%, 4.74%, 6.96%, and 4.26% of the observations, and other lenders cover a share of 1%-2% of the observations per lender.

5.1. Differences in the rating levels across racial groups

First, in our matching game model, the higher likelihood of fintech usage among minority-owned restaurants can be generated through the combination of the self-selection effect or the crowding-out effect and the difference in rating levels across racial groups. We have the self-selection effect of higher-rated borrowers into fintech lenders if higher-rated borrowers have a higher payoff when matched with fintech lenders than with banks. Similarly, higher-rated borrowers without bank lending relationships are crowded out to fintech lenders by lower-rated borrowers with bank lending relationships due to the additional utility generated by lending relationships. If minority-owned restaurants have higher ratings on average, then we expect to see more minority-owned restaurants using fintech lenders.

[INSERT TABLE 4 AROUND HERE]

However, we find little empirical evidence supporting this channel. On one hand, Table 4 shows that borrowers with higher ratings are more likely to use fintech lenders in the 2020 wave. The coefficient on the fintech indicator is positive and statistically significant at 1% in all specifications, which is consistent with our model's prediction that higher-rated borrowers self-select into fintech lenders or the prediction of the crowding-out effect of lower-rated borrowers with lending relationships.[30] The coefficient on the fintech indicator becomes insignificant in the 2021 wave. As the 2021 wave is a supplement to the 2020 wave, it is reasonable that the effect is attenuated. On the other hand, overall minority-owned restaurants have lower ratings.

5.2. Minority borrowers and previous lending relationships

Second, it is possible that a smaller share of minority-owned restaurants have lending relationships, and therefore the minority-owned restaurants are relatively more affected by the crowding-out effects of restaurants with lending relationships. This explanation speaks to one type of racial inequality in the small business credit market that is caused by previous lending

[30] Without further information, we cannot empirically distinguish between the two explanations.

relationships. We test this hypothesis by comparing the share of borrowers with lending relationships for minority- and non-minority-owned restaurants.

[INSERT TABLE 5 AROUND HERE]

Table 5 reports the results for the matched sample for the 2020 (Panel A) and 2021 (Panel B) waves. In the 2020 wave, the minority recipients, compared with non-minority recipients, are less likely to have previous lending relationships and have less intensive lending relationships. Column (1) shows that after controlling for other business characteristics, Asian (Hispanic)-owned restaurants are 0.72% (1.11%) less likely to have lending relationships, amounting to 24% (37%) of the sample mean, where lending relationships are proxied by a dummy variable that equals one if the borrower has at least one SBA 7(a) or 504 loan from 2009 to 2019. In column (2), we further control for city fixed-effects, and the likelihood difference enlarges to 1.00% for Asian-owned restaurants but narrows to 1.03% for Hispanic-owned restaurants. In columns (3) and (4), we measure the intensity of lending relationships using the number of the previous SBA 7(a) and 504 loans the borrower had during 2009-2019. In columns (5) and (6), we build the measure using the dollar value of the previous SBA loans. Results are similar to specifications using the dummy variable of lending relationships. Coefficients before the racial groups become insignificant in most specifications in the 2021 wave. Results for the full sample are reported in Online Appendix Table B5 and are similar.

[INSERT TABLE 6 AROUND HERE]

Moreover, Table 6 shows that restaurants without lending relationships are more likely to use fintech lenders in both the 2020 and 2021 waves. The substitution effect is even stronger in the 2021 wave. Results are consistent across different measures of the lending relationships. Table 6 presents results on the matched sample and Online Appendix Table B6 presents results on the full sample where we observe a similar substitution effect of fintech lenders for borrowers without lending relationships.

Combining these two pieces of evidence, our findings support that the share of borrowers with lending relationships leads to a difference in the fintech usage rate. Overall, we find that minority borrowers have a lower level of previous lending relationships in the SBA programs, and borrowers without lending relationships are more likely to substitute traditional lenders with fintech lenders.

5.3. Business capital of borrowers

Third and perhaps more important, our model predicts that the racial bias in the value of the borrower-lender matches leads to a difference in the minority-non-minority rating gap between fintech and non-fintech lenders. In the previous section, we provide empirical evidence on the existence of such a double difference in rating levels. In this section, we further explore what contributes to the existence of racial disparities.

In the preference for technology scenario, our model predicts that a larger difference in the preference for technology between the minority and non-minority borrowers will translate into a larger difference in the minority-non-minority rating gap between fintech and non-fintech lenders. As there is no good measure of the preference for technology, we cannot directly test this prediction. Instead, we indirectly test the hypothesis by studying whether an increase in the level of the business capital by the borrower mitigates the difference in the minority-non-minority rating gap between fintech and non-fintech lenders.

Minority-owned restaurants tend to have a business model that is more informal and less familiar to outsiders. Because business capital can provide more information about the restaurant, it can be soft assets that serves as a role of collateral (Hochberg, Serrano, and Ziedonis, 2018; Davis, Morse, and Wang, 2020). As a result, borrowers with a higher level of business capital can rely less on technology in the lending process. In other words, the business capital of borrowers may be a way to mitigate the racial bias in the small business lending market.

We use the total number of ratings during our entire analysis sample period from April 2018 to March 2021 as a proxy for business capital.[31] For two otherwise similar restaurants, the one with more reviews has more available information and can be seen as having a better reputation.

[INSERT TABLE 7 AROUND HERE]

[31] Shi (2021) uses the firm size as a proxy for business capital to study how business capital increases the likelihood of being a PPP recipient.

Table 7 reports the results on the role of business capital for the matched sample. The coefficients before the triple interaction between the fintech lender indicator, the minority borrower indicator, and business capital are positive and significant at the 1% level in all specifications for Asian- and Hispanic-owned restaurants in the 2020 wave. Column (1) shows that an increase of 100 reviews during our entire analysis sample period, which amounts to around one unit of sample deviation, is associated with a 0.11 star (or 1.38 times the original racial gap) smaller fintech-minority rating gap for the Asian recipients in the 2020 wave. Column (2) controls for city-month fixed effects and the results are similar. In columns (3) and (4), we measure the racial gap using ratings for the during -- Covid period and the results are robust.

Columns (5) through (8) present the results for the 2021 wave where we observe coefficients of almost twice as big as the coefficients in the 2020 wave for Asian-owned restaurants. Coefficients before the triple interaction terms with Hispanic-owned restaurants become insignificant. Results on the full sample are reported in the Online Appendix Table B7 and are consistent.

Overall, our findings suggest that restaurants with a higher level of business capital are associated with a lower level of racial discrimination. This is in alignment with a racial gap in tech-preference on the borrower side contributing to the difference in the minority-non-minority rating gap between fintech and non-fintech lenders.

5.4. Geographic scope of lenders

Finally, another prediction in the lending relationship scenario in our model is that the difference in the value of lending relationships between the minority and non-minority borrowers is also positively related to the minority-non-minority rating gap between fintech and non-fintech lenders. We test this hypothesis by investigating whether a decrease in the level of the lender attention aggravates the difference in the minority-non-minority rating gap between fintech and non-fintech lenders.

Discrimination can result in a lower value of lending relationships for minority-owned businesses. As the value of lending relationships tends to be formed and reinforced through interactions, less lender attention allocated to the region where the borrower is located can exaggerate the racial gap in the value of lending relationships. As a result, we observe a larger racial gap for lenders with a lower level of attention to individual borrower regions.

We use the relative geographic lending scope (*GS_r*) as a proxy for the relative lender attention allocated to a given geographic region. *GS_r* is calculated as the total number of zip codes divided by the total number of cities that the lender covers in the entire PPP loan sample. For this part of the analysis, we drop CDFIs/CDCs as they may have specific regional requirements.

[INSERT TABLE 8 AROUND HERE]

Table 8 reports the results on the impact of relative geographic lending scope (GS_r) for the matched sample. The coefficients before the triple interaction between the fintech lender indicator, the minority borrower indicator, and GS_r are negative in specifications with a significance level of at least 5%. Column (1) shows that an increase of one location of GS_r is associated with a 0.06 star (or 0.75 times the original racial gap) larger fintech-minority rating gap for the Asian recipients in the 2020 wave. Results with and without city-month fixed effects are similar. In addition, results on the full sample are reported in the Online Appendix Table B8 and are consistent.

To further demonstrate that it is the *relative* geographic lending scope that affects the racial bias, we re-do the analysis by including both the geographic lending scope at the city level (GS_{city}) and the geographic lending scope at the zip-code level (GS_{zip}). Results are presented in Online Appendix Table B9. Consistent with the results using the relative geographic lending scope (GS_r), the coefficients are positive for the triple interaction with GS_{city} and negative for the triple interaction with GS_{zip}.

Overall, our findings indicate that restaurants matched with lenders with a higher level of attention in their geographic area are associated with a lower level of racial discrimination. This is consistent with the existence of a racial bias in the value of lending relationships.

6. Alternative Explanations

6.1. Other lender types

In this section, we study other types of lenders, including first-time banks, credit unions, community development financial institutions and community development corporations, non-federally-insured lenders, and savings & loan associations, to see if non-technology-related features of fintech lenders coincidentally lead to our main empirical findings.[32]

[32] For demonstration purposes, we present the results of the rating gap using the matched sample. Results on the full sample are in Online Appendix Table B10 and are in alignment with the findings for the matched sample.

6.1.1. First-time bank participants

First, it is possible that fintech lenders are new entrants to SBA programs and therefore attract a different segment of borrowers. We test this hypothesis by studying the 672 first-time participants out of the 4,131 PPP bank sample, which account for around 4.04% of the loans.

[INSERT TABLE 9 AROUND HERE]

We do not find supporting evidence. Table 9 Panel A shows that the relationship between minority borrowers and the likelihood of being matched with newly entered banks is significantly lower for Asian-owned restaurants and insignificant for African American- and Hispanic-owned restaurants. Moreover, Panel B shows that the minority-non-minority rating gap is insignificant or more positive for fintech lenders compared with non-fintech lenders. The results indicate that, unlike fintech lenders, if anything, first-time banks attract a segment of higher-rated minority-owned restaurants than non-minority-owned restaurants.

6.1.2. Credit unions

Second, it is possible that, because fintech lenders tend to have more flexible loan terms than banks, they may develop a different customer base. We test this hypothesis by studying another type of bank alternatives: credit unions. Credit unions are the second largest type of bank alternatives among PPP lenders, composing 409 out of the 3,658 lenders that we find a match with FFEIC, accounting for 3.48% of the loans. If our documented minority-non-minority gap is because of the unobserved characteristic of borrowers that prefer lenders offering more attractive loan terms, (and not due to racial discrimination), we should observe a similar pattern for the comparison between credit unions and banks as for the comparison between fintech lenders and banks.

[INSERT TABLE 10 AROUND HERE]

Table 10 Panel A shows that Asian-owned restaurants are less likely to use credit unions, which is opposite of the results for fintech lenders. African American- and Hispanic-owned restaurants are more likely to use credit unions. However, Panel B reports a more negative difference in the minority-non-minority rating gap between fintech and non-fintech lenders for Asian-owned restaurants. The same signs of the coefficients of the credit union usage likelihood and the double difference in rating levels suggest that the segment of minority borrowers served by credit unions are those who have a better evaluation with banks, rather than those who are more undervalued. We do not find the same results for credit unions as for fintech lenders.

6.1.3. Community development financial institutions/corporations

Third, we investigate whether fintech lenders mimic the role of community development financial institutions (CDFIs) and community development corporations (CDCs). There are 54 CDFIs/CDCs in the sample of 4,185 lenders, accounting for 0.72% of the loans. We exclude fintech lenders and other non-banks to make a clean comparison.

[INSERT TABLE 11 AROUND HERE]

At first glance, CDFIs and CDCs play a similar role as fintech lenders. Table 11 Panel A shows that minority-owned restaurants of all racial groups are more likely to use CDFIs/CDCs in the 2020 wave. Results become insignificant and even significantly negative for Asian-owned restaurants in the 2021 wave. However, in Panel B, we find no significant results on the double-difference in rating levels, except for Asians in the 2020 wave using the pre-Covid ratings. Our findings imply that while CDFIs and CDCs are able to cover more minority-owned businesses, they play a limited supplemental role in extending credits to minority-owned businesses that are more undervalued by traditional lenders.

6.1.4. Non-federally-insured lenders and savings & loan associations

In addition, we present results on two other types of lenders that might play a similar role as fintech lenders in the Online Appendix: the 11 non-federally-insured lenders (Table B11) and the 25 savings & loan associations (Table B12).

First, our racial disparity results might be driven by regulatory differences in federally-insured and non-federally-insured lenders.[33] For example, minority borrowers might have received

[33] The PPP Lender Information Sheet states that all federally insured depository institutions, federally insured credit unions, and Farm Credit System institutions are eligible to participate in this program. For non-insured lenders, as most fintech lenders are, they need to apply for approval to be enrolled in the program.

information about PPP loans later and applied after more non-insured lenders participated. Second, fintech lenders are also well-known as an alternative option of mortgages and might be more familiar to lower-rated minority-owned businesses. To address this possibility, we study savings & loan associations (S&Ls) who mainly offer affordable mortgages as a comparison group to banks. However, we do not find similar patterns for non-federally-insured lenders or S&Ls as for fintech lenders. If anything, we find a more positive difference in the minority-non-minority rating gap between fintech and non-fintech lenders.

To recap, in this section, we show that for other types of lenders, there is no consistent evidence that supports our model's prediction on the negative double difference in rating levels. Unlike fintech lenders, we do not find evidence that first-time bank participants, credit unions, CDFIs/CDCs, non-federally-insured lenders, or S&Ls are likely to provide credit accesses to the segment of minority borrowers that are more undervalued in the traditional market.

6.2. Loan approval speed

Another alternative explanation of our racial disparity results is a difference among borrowers in the preference of loan processing speed that coincides with using fintech lenders. Online Appendix Table B13 shows that on average fintech lenders have a higher loan processing capacity. In addition, the existing literature documents that fintech lenders process mortgage applications much faster than other lenders (Fuster et. al. 2019). Therefore, it might be that a different group of minority and non-minority borrowers prefer quicker loan processing and turn to fintech lenders disproportionally.

[INSERT TABLE 12 AROUND HERE]

Table 12 shows the regression results that compare the difference in the number of days needed to get the loan approved from the beginning of each PPP wave between the minority and non-minority borrowers matched with fintech and non-fintech lenders.[34] In the 2020 wave, the

https://home.treasury.gov/system/files/136/PPP%20Lender%20Information%20Fact%20Sheet.pdf

[34] The measure based on approval dates is not the exact loan processing speed of the lenders. However, we do not have information on the application dates, and the measure using approval dates provides information on borrowers' preference for loan processing speed given that all the loan application starting dates are the same for all lenders.

double difference in approval days is insignificant for the African American- and Hispanic-owned restaurants. For Asian-owned restaurants, double difference in approval days is positive and significant at the 1% level. For example, column (1) reports that the Asian-non-minority gap in approval days is 2.23 days longer for the fintech borrowers than for non-fintech borrowers. This indicates that minority borrowers who turn to fintech lenders waited relatively longer compared with non-minority borrowers than those who reach out to non-fintech lenders, consistent with a higher barrier that minority borrowers face to access to the traditional credit market.

Interestingly, consistent with a reduction in racial basis in the 2021 wave we document in the previous section using the rating gap, there are also improvements in waiting time. The coefficients before the interaction terms between the racial group and fintech indicators become negative for Asian- (8.11 days shorter) and Hispanic-owned restaurants (8.72 days shorter). Results on African American- owned restaurants are insignificant. One explanation for the shorter waiting period for the 2021 wave could be that fintech lenders improved their loan processing speed, given that fintech platforms are more adaptive for similar lending tasks in the following year. Another is that or the group of minority borrowers supplemented by the 2021 wave were no longer those overlooked by the traditional credit market.

In robustness checks reported in Online Appendix Table B14, we address the issue that fintech lenders were not allowed to participate at the beginning of the 2020 wave. We limit the sample period to 1) after the official approval date of fintech entry, and 2) the second tranche. Results are robust and even stronger when limited to the second tranche.

Online Appendix Table B15 reports results on the robustness check of Table 3 where we control for the approval date fixed effects. This gives the estimation of the double difference in rating levels for loans approved on the same day, and thus rules out differences due to the borrower's position in the PPP application queue. Coefficients before the interaction terms between the racial group and fintech indicators are very close to those reported in Table 3, which implies that the racial disparities that we demonstrate *do not* come from a difference in loans approved earlier or later.

Overall, our findings suggest that minority borrowers turned to fintech lenders in the PPP program *not* because they have a higher preference for getting the loan earlier. In fact, our results show that minority borrowers who applied for a loan through fintech lenders had a longer waiting time in the 2020 wave.

7. Conclusion

This paper studies whether fintech lenders can serve minority-owned small businesses that are less valued in the traditional credit market. We use the Paycheck Protection Program as a laboratory and a linked dataset on the PPP loans and a large-scale national-wide sample of restaurants on yelp.com to study the question.

We first document that minority-owned businesses are more likely to use fintech lenders, which is consistent with the existing literature. More importantly, we provide evidence showing that the racial disparity in using fintech versus traditional lenders is very likely to be attributed to deep-rooted racial gaps in the small business lending market. Compared with fintech lenders, traditional lenders are more likely to lend to minority-owned businesses with previous lending relationships, and of higher ratings. Given the fully government-guaranteed nature of the PPP program, these findings point to unequal credit provision driven by taste-based discriminations.

Whether governments should extend credit access to the minority-owned businesses underserved by traditional lenders is a normative question. On one hand, these minority-owned businesses are of lower rating levels and are likely to have lower revenue (Luca (2016)). On the other hand, they are part of the fabric of their communities, employing local residents and supporting civic causes. Moreover, the existing literature finds that SBA loans have positive effects on firm growth and productivity (Krishnan, Nandy, and Puri, 2015; Brown and Earle, 2017), which implies that the lower operational performance of these minority-owned businesses may exactly due to being previously excluded from government loan programs.

This paper studies the first large-scale government loan program where major fintech lending platforms, such as Paypal, Kabbage, and Funding Circle, are allowed to be eligible lenders. Our study has important policy implications that speak to the debate on whether to allow for the participation of fintech lenders in fully or partially guaranteed government loan programs. Our findings suggest that there are systematic biases and blind spots in the traditional loan distribution channel and that can be covered by fintech lenders. This has implications beyond the Covid-19 period. Whether the credit access provided by fintech lenders improves the financial and operational performance of those underserved borrowers is an interesting topic for future research.

In addition, the impact of the introduction of fintech lenders on traditional lenders is also a promising avenue for future research.

References

Agarwal, S. and Hauswald, R., 2010. Distance and private information in lending. *The Review of Financial Studies*, *23*(7), pp.2757-2788.

Alekseev, G., Amer, S., Gopal, M., Kuchler, T., Schneider, J.W., Stroebel, J. and Wernerfelt, N.C., 2020. The effects of COVID-19 on Us small businesses: Evidence from owners, managers, and employees (*No. w27833*). National Bureau of Economic Research.

Alstadsæter, A., Bjørkheim, J.B., Kopczuk, W. and Økland, A., 2020. Norwegian and US policies alleviate business vulnerability due to the COVID-19 shock equally well. *National Tax Journal*, *73*(3), pp.805-828.

Amiram, D. and Rabetti, D., 2020. The relevance of relationship lending in times of crisis. *Available at SSRN 3701587*.

Anderson, M. and Magruder, J., 2012. Learning from the crowd: Regression discontinuity estimates of the effects of an online review database. *The Economic Journal*, *122*(563), pp.957-989.

Arrow, K., 1971. The theory of discrimination. Princeton University, Department of Economics. *Industrial Relations Section*, *403*.

Asiedu, E., Freeman, J. A., & Nti-Addae, A. (2012). Access to credit by small businesses: How relevant are race, ethnicity, and gender?. *American Economic Review*, *102*(3), 532-37.

Atkins, R., Cook, L. & Seamans, R., 2021. Discrimination in lending? Evidence from the Paycheck Protection Program. *Small Bus Econ*.

Autor, D., Cho, D., Crane, L.D., Goldar, M., Lutz, B., Montes, J., Peterman, W.B., Ratner, D., Villar, D. and Yildirmaz, A., 2020. An evaluation of the paycheck protection program using administrative payroll microdata. *Unpublished manuscript*, *22*.

Azevedo, E.M. and Hatfield, J.W., 2018. Existence of equilibrium in large matching markets with complementarities. *Available at SSRN 3268884*.

Balyuk, T., Prabhala, N.R. and Puri, M., 2020. Indirect costs of government aid and intermediary supply effects: Lessons from the Paycheck Protection Program (*No. w28114*). National Bureau of Economic Research.

Bartik, A.W., Cullen, Z.B., Glaeser, E.L., Luca, M., Stanton, C.T. and Sunderam, A., 2020. The targeting and impact of Paycheck Protection Program loans to small businesses (*No. w27623*). National Bureau of Economic Research.

Bartlett, R., Morse, A., Stanton, R. and Wallace, N., 2021. Consumer-lending discrimination in the FinTech era. *Journal of Financial Economics*.

Bartlett, R.P. and Morse, A., Forthcoming. Small business survival capabilities and policy effectiveness: Evidence from Oakland. *Journal of Financial and Quantitative Analysis*, special issue on Covid research.

Bates, Timothy. "Financing small business creation: The case of Chinese and Korean immigrant entrepreneurs." *Journal of Business Venturing* 12.2 (1997): 109-124.

Bates, T. and Robb, A., 2013. Greater access to capital is needed to unleash the local economic development potential of minority-owned businesses. *Economic Development Quarterly*, *27*(3), pp.250-259.

Bates, T. and Robb, A., 2015. Has the Community Reinvestment Act increased loan availability among small businesses operating in minority neighbourhoods?. *Urban Studies*, *52*(9), pp.1702-1721.

Beaumont, P., Tang, H. and Vansteenbergh, E., 2021. The role of FinTech in small business lending. *Working paper*.

Becker, G.S., 1957. The economics of discrimination. *University of Chicago press*.

Berger, A.N. and Demirgüç-Kunt, A., 2021. Banking Research in the Time of COVID-19. *Journal of Financial Stability*, p.100939.

Berger, A.N., Freed, P.G., Scott, J.A. and Zhang, S., 2021. The Paycheck Protection Program (PPP) from the Small Business Perspective: Did the PPP Help Alleviate Financial and Economic Constraints?. *Available at SSRN 3908707*.

Berger, A.N., Karakaplan, M.U. and Roman, R.A., 2021. Whose bailout is it anyway? Political connections of small businesses vs. banks in PPP bailouts. *Available at SSRN 3920758*.

Bernstein, S. and Sheen, A., 2016. The operational consequences of private equity buyouts: Evidence from the restaurant industry. *The Review of Financial Studies*, *29*(9), pp.2387-2418.

Blanchard, L., Zhao, B. and Yinger, J., 2008. Do lenders discriminate against minority and woman entrepreneurs?. *Journal of Urban Economics*, *63*(2), pp.467-497.

Blanchflower, D.G., Levine, P.B. and Zimmerman, D.J., 2003. Discrimination in the small-business credit market. *Review of Economics and Statistics*, *85*(4), pp.930-943.

Brown, J.D. and Earle, J.S., 2017. Finance and growth at the firm level: Evidence from SBA loans. *The Journal of Finance*, *72*(3), pp.1039-1080.

Buffington, C., Chapman, D., Dinlersoz, E., Foster, L. and Haltiwanger, J., 2021. High Frequency Business Dynamics in the United States during the COVID-19 Pandemic, mimeo.

Cavalluzzo, K.S. and Cavalluzzo, L.C., 1998. Market structure and discrimination: The case of small businesses. *Journal of Money, Credit and Banking*, pp.771-792.

Cavalluzzo, K.S., Cavalluzzo, L.C. and Wolken, J.D., 2002. Competition, small business financing, and discrimination: Evidence from a new survey. *The Journal of Business*, *75*(4), pp.641-679.

Cavalluzzo, K. and Wolken, J., 2005. Small business loan turndowns, personal wealth, and discrimination. *The Journal of Business*, *78*(6), pp.2153-2178.

Chernenko, S. and Scharfstein, D.S., 2021. Racial Disparities in the Paycheck Protection Program. *Available at SSRN 3907575*.

Cherry, S.F., Jiang, E.X., Matvos, G., Piskorski, T. and Seru, A., 2021. Government and private household debt relief during covid-19 (*No. w28357*). National Bureau of Economic Research.

Cororaton, A. and Rosen, S., 2020. Public firm borrowers of the US Paycheck Protection Program. *Available at SSRN 3590913*.

Couch, K.A., Fairlie, R.W. and Xu, H., 2020. Early evidence of the impacts of COVID-19 on minority unemployment. *Journal of Public Economics*, *192*, p.104287.

Cumming, D.J., Farag, H., Johan, S. and McGowan, D., 2019. The Digital Credit Divide: Marketplace Lending and Entrepreneurship. *Journal of Financial and Quantitative Analysis, forthcoming*.

D'Acunto, F., Ghosh, P., Jain, R. and Rossi, A.G., 2020. How Costly are Cultural Biases?. *Available at SSRN 3736117*.

Davis, D.R., Dingel, J.I., Monras, J. and Morales, E., 2019. How segregated is urban consumption?. *Journal of Political Economy*, *127*(4), pp.1684-1738.

Davis, J., Morse, A. and Wang, X., 2020. The leveraging of silicon valley (*No. w27591*). National Bureau of Economic Research.

Denes, M., Lagaras, S. and Tsoutsoura, M., 2021. First Come, First Served: The Timing of Government Support and Its Impact on Firms. *Available at SSRN 3845046*.

Duchin, R. and Hackney, J., Forthcoming. Buying the Vote? The economics of electoral politics and small business loans. *Journal of Financial and Quantitative Analysis.*

Duchin, R., Martin, X., Michaely, R. and Wang, H.I., 2021. Concierge Treatment from Banks: Evidence from the Paycheck Protection Program. *Available at SSRN 3775276*.

Erel, I. and Liebersohn, J., 2020. Does Fintech substitute for banks? Evidence from the Paycheck Protection Program (*No. w27659*). National Bureau of Economic Research.

Fairlie, R., 2020. The impact of COVID-19 on small business owners: Evidence from the first three months after widespread social-distancing restrictions. *Journal of Economics & Management Strategy*, *29*(4), pp.727-740.

Fairlie, R. and Fossen, F.M., 2021a. Did the Paycheck Protection Program and Economic Injury Disaster Loan Program get disbursed to minority communities in the early stages of COVID-19?. *Small Business Economics*, pp.1-14.

Fairlie, R. and Fossen, F.M., 2021b. The early impacts of the COVID-19 pandemic on business sales. *Small Business Economics*, pp.1-12.

Fairlie, R. and Fossen, F.M., 2021c. Paycheck Protection Program and Disbursement to Minority Communities in 2021. *Mimeo*.

Fairlie, R.W. and Robb, A.M., 2008. Race and entrepreneurial success. *Cambridge, MA: The*.

Farronato, C., Fradkin, A., Larsen, B. and Brynjolfsson, E., 2020. Consumer protection in an online world: An analysis of occupational licensing (*No. w26601*). National Bureau of Economic Research.

Fazio, C.E., Guzman, J., Liu, Y. and Stern, S., 2021. How is COVID Changing the Geography of Entrepreneurship? Evidence from the Startup Cartography Project (*No. w28787*). National Bureau of Economic Research.

Fuster, A., Goldsmith-Pinkham, P., Ramadorai, T. and Walther, A., forthcoming. Predictably unequal? The effects of machine learning on credit markets. *Journal of Finance*.

Fuster, A., Plosser, M., Schnabl, P. and Vickery, J., 2019. The role of technology in mortgage lending. *The Review of Financial Studies*, 32(5), pp.1854-1899.

Gopal, M. and Schnabl, P., 2020. The rise of finance companies and FinTech lenders in small business lending. *Working Papers*, NYU Stern School of Business.

Granja, J., Makridis, C., Yannelis, C. and Zwick, E., 2020. Did the Paycheck Protection Program hit the target? (No. w27095). *National Bureau of Economic Research*.

Griffin, J.M., Kruger, S. and Mahajan, P., 2021. Did FinTech Lenders Facilitate PPP Fraud?. *Available at SSRN 3906395*.

Hochberg, Y.V., Serrano, C.J. and Ziedonis, R.H., 2018. Patent collateral, investor commitment, and the market for venture lending. *Journal of Financial Economics*, *130*(1), pp.74-94.

Howell, S.T., Kuchler, T., Snitkof, D., Stroebel, J. and Wong, J., 2021. Racial Disparities in Access to Small Business Credit: Evidence from the Paycheck Protection Program (No. w29364). *National Bureau of Economic Research*.

Humphries, J.E., Neilson, C.A. and Ulyssea, G., 2020. Information frictions and access to the Paycheck protection program. *Journal of Public Economics*, *190*, p.104244.

Jagtiani, J., Lemieux, C., 2018. Do fintech lenders penetrate areas that are underserved by traditional banks? *Journal of Economics and Business* 100, 43–54.

Krishnan, K., Nandy, D.K. and Puri, M., 2015. Does financing spur small business productivity? Evidence from a natural experiment. *The Review of Financial Studies*, *28*(6), pp.1768-1809.

Li, L. and Strahan, P., Forthcoming. Who supplies PPP loans (And does it matter)? Banks, relationships and the COVID Crisis. *Journal of Financial and Quantitative Analysis*.

Luca, M., 2016. Reviews, reputation, and revenue: The case of Yelp. com. (March 15, 2016). *Harvard Business School NOM Unit Working Paper*, (12-016).

Mayzlin, D., Dover, Y. and Chevalier, J., 2014. Promotional reviews: An empirical investigation of online review manipulation. *American Economic Review*, *104*(8), pp.2421-55.

Mills, K., McCarthy, B., 2016. The state of small business lending: Innovation and technology and the implications for regulation. Harvard Business School Entrepreneurial Management Working Paper pp. 17–042.

Phelps, E. S. (1972). The statistical theory of racism and sexism. *American Economic Review*, 62(4), 659-661.

Reimers, I. and Waldfogel, J., 2021. Digitization and pre-purchase information: the causal and welfare impacts of reviews and crowd ratings. *American Economic Review, 111*(6), pp.1944-71.

SBCS, 2021. Small Business Credit Survey 2021 Report.

Shi, C.Y., 2021. A Story of Human Capital: Why the Paycheck Protection Program Had Huge Geographic Disparities (*Mimeo, Harvard University*).

Tareque, I., Orozco, M., Oyer, P. and Porras, J., 2021. US Black-Owned Businesses: Pre-Pandemic Trends & Challenges. *Center for Entrepreneurial Studies, Stanford Graduate School of Business*.

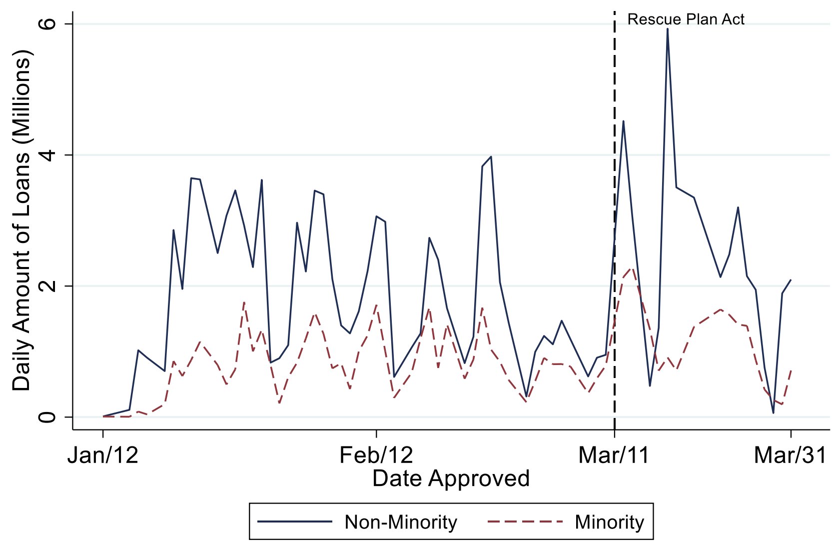
U.S. Census Bureau. 2016. "Survey of business owners (SBO) -survey results: 2012"

Wang, J., and D. H. Zhang. 2020. The cost of banking deserts: Racial disparities in access to PPP lenders and their equilibrium implications. *Working paper*. Harvard *University*.

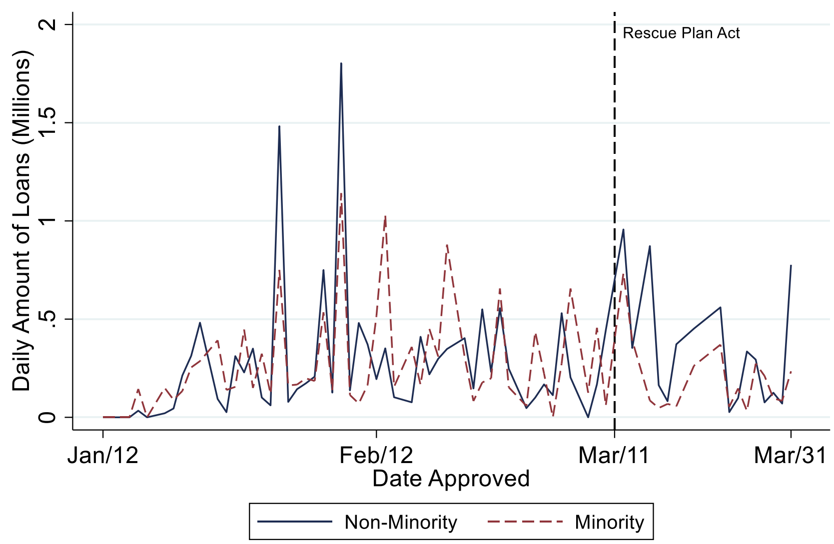
Xu, Y., Armony, M. and Ghose, A., 2021. The interplay between online reviews and physician demand: An empirical investigation. *Management Science*.

Yang, K., 2021. Trust as an entry barrier: Evidence from fintech adoption. *Available at SSRN 3761468*.

Figures



(a) 2021 PPP, Non-Fintech Lenders



(b) 2021 PPP, Fintech Lenders

Figure 1: Minority- and Non-Minority-owned Businesses in the 2021 PPP Fintech vs. Non-Fintech

This figure plots the daily dollar value of PPP loans received by minority- and non-minority-owned restaurants that were processed by non-fintech (Panel (a)) and fintech (Panel (b)) lenders in the 2021 PPP wave for our sample. The 2021 wave spans the period from January 12, 2021 to March 31, 2021. The y-axis represents the daily dollar value of loans processed (in USD millions), and the x-axis represents the loan approval date. The blue solid line plots non-minority-owned restaurants and the red dashed line plots minority-owned restaurants. The vertical dashed line indicates the implementation of the American Rescue Plan Act of 2021 on March 11, 2021.

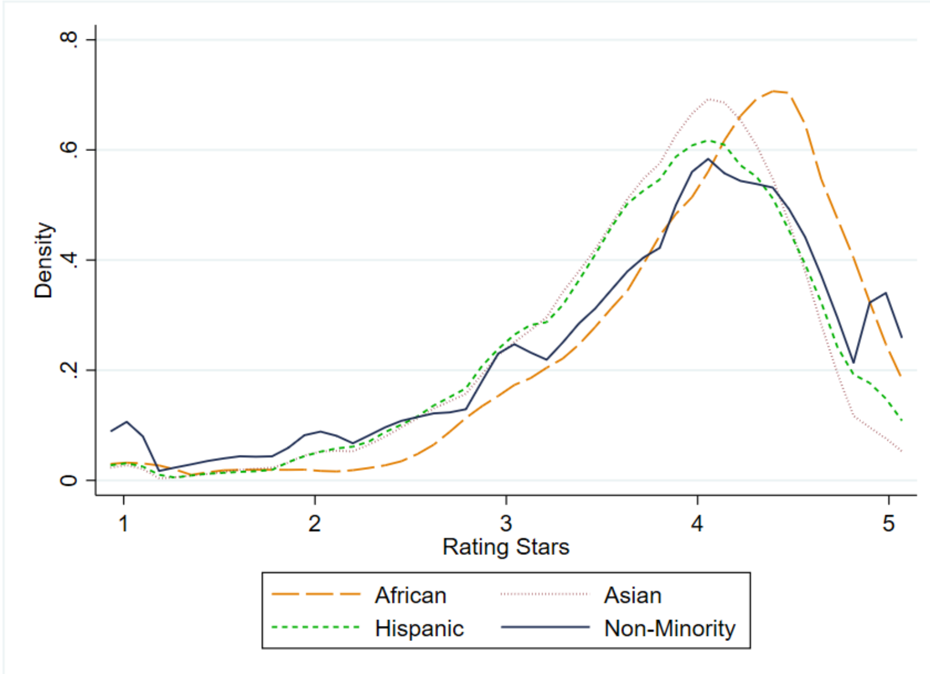
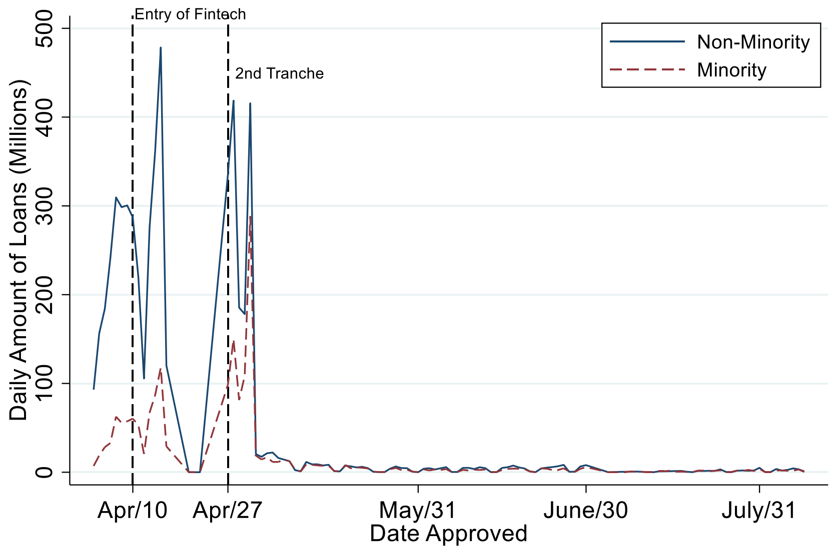
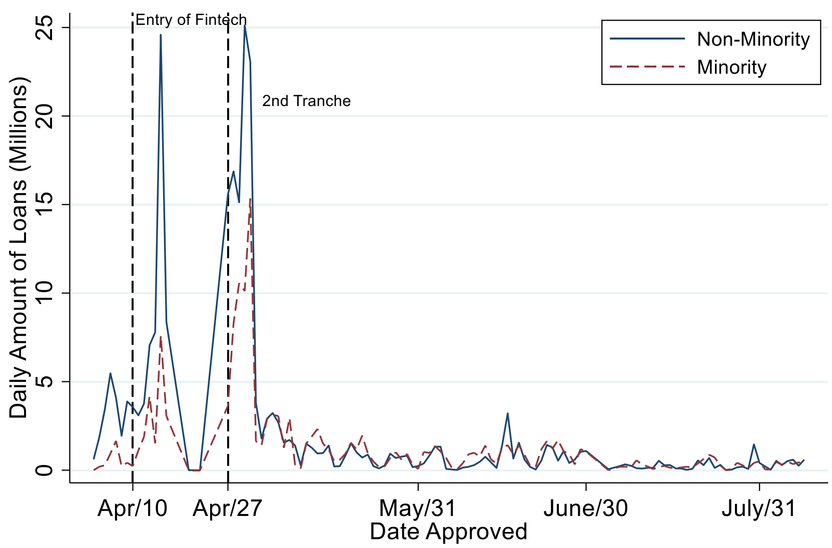


Figure 2: Distribution of Restaurant Ratings across Borrower Racial Groups

This figure plots the density of restaurant ratings for each racial group using data on customer ratings from yelp.com. For each restaurant in our linked sample, we calculate the mean of the monthly average of ratings from April 2018 to March 2021.



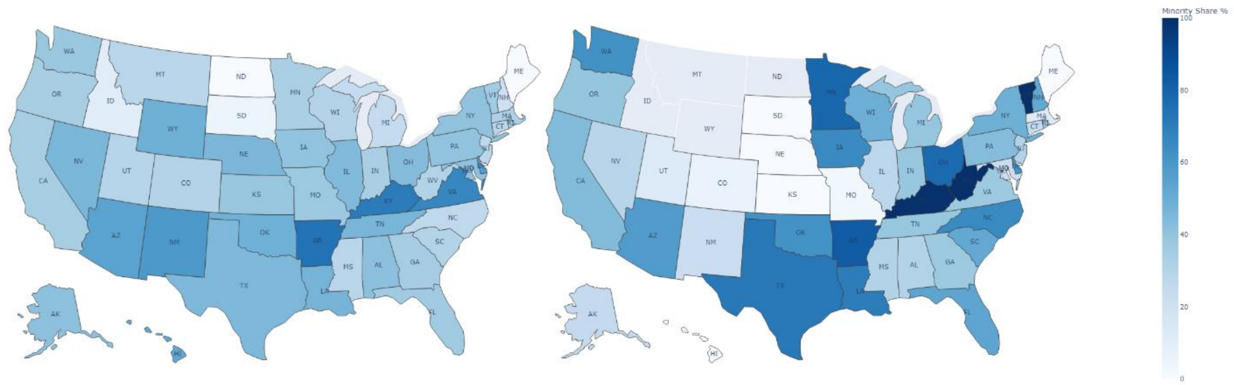
(a) 2020 PPP, Non-Fintech Lenders



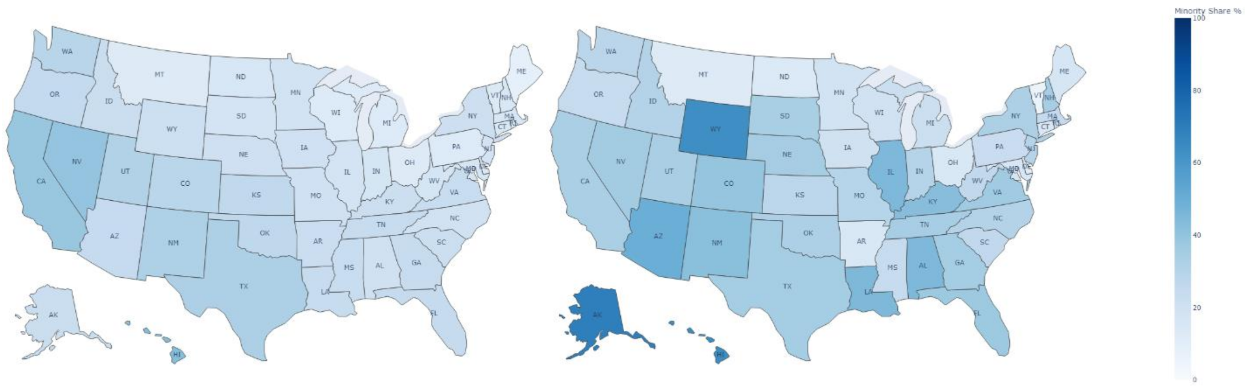
(b) 2020 PPP, Fintech Lenders

Figure 3: Minority- and Non-Minority-owned Businesses in the 2020 PPP Fintech vs. Non-Fintech (Dollar Value)

This figure plots the daily dollar value of PPP loans received by minority- and non-minority-owned restaurants that are processed by non-fintech (Panel (a)) and fintech (Panel (b)) lenders in the 2020 PPP wave for our sample. The 2020 wave spans the period from April 3, 2020 to August 8, 2020. The y-axis represents the daily dollar value of loans processed (in USD millions), and the x-axis represents the loan approval date. The blue solid line plots the non-minority-owned restaurants and the red dashed line plots the minority-owned restaurants. The first vertical dashed line indicates the entry of fintech lenders on April 10, 2020 and the second vertical dashed line indicates the beginning of the second tranche of the 2020 PPP on April 27, 2020.



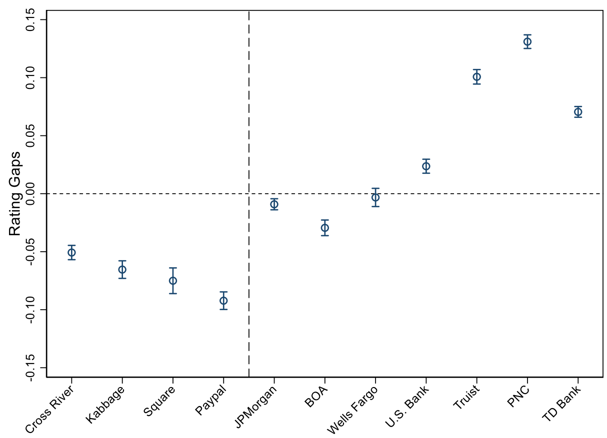
(a) Minority Share (Fintech) in the 2020 PPP (b) Minority Share (Fintech) in the 2021 PPP



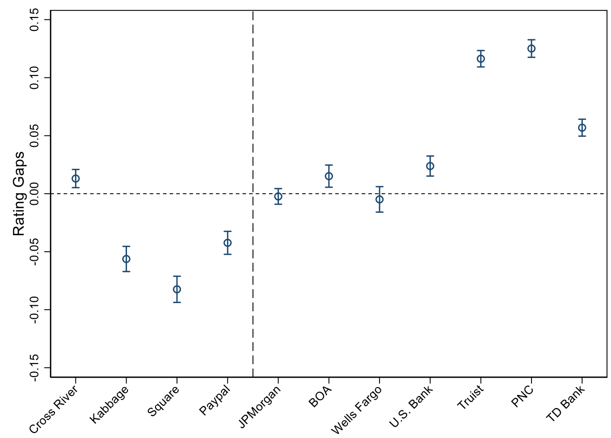
(c) Minority Share (Non-Fintech) in the 2020 PPP (d) Minority Share (Non-Fintech) in the 2021 PPP

Figure 4: Percentage of Loans Distributed to Minority-owned Businesses Fintech vs. Non-Fintech (Dollar Value)

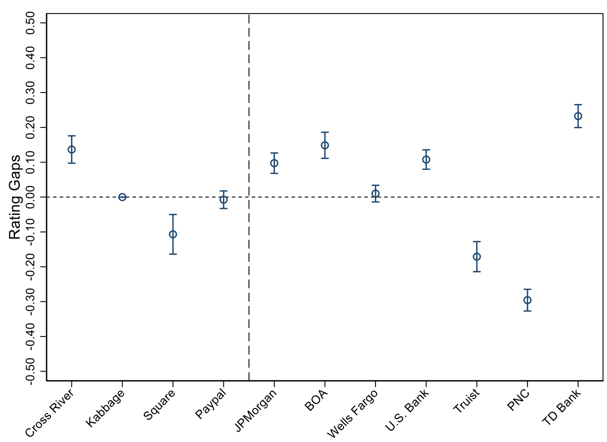
This figure plots the share of loan dollar value distributed to minority-owned businesses processed by fintech (Panels (a) and (b)) and non-fintech (Panels (c) and (d)) lenders in the 2020 and 2021 waves, based on our sample. The *Minority Shares* range from 0% (the lightest blue) to 100% (the darkest blue).



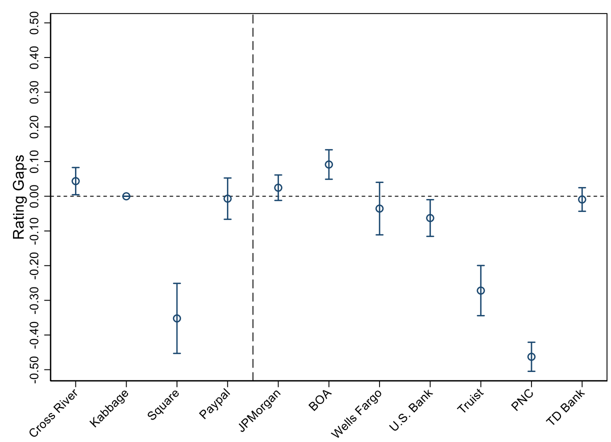
(a) Before-Covid Ratings, 2020 PPP Recipients



(b) During-Covid Ratings, 2020 PPP Recipients



(c) Before-Covid Ratings, 2021 PPP Recipients



(d) During-Covid Ratings, 2021 PPP Recipients

Figure 5: Minority-Non-Minority Rating Gap (Asian-owned)
Fintech vs. Non-Fintech

This figure plots the minority-non-minority rating gap for Asian-owned restaurants in the 2020 wave using historical ratings before the Covid-19 crisis (Panel (a)) and ratings during the Covid-19 crisis (Panel (b)), and for Asian-owned restaurants in the 2021 wave using the before-Covid ratings (Panel (c)) and during-Covid ratings (Panel (d)). The y-axis represents the coefficients before the interaction terms between the racial group indicator and lender indicators from the regressions as in Table 3, except that we decompose the fintech indicator into several dummies for each big fintech lender and bank. The x-axis represents each lender. We plot the biggest four fintech lenders in our sample: Cross River Bank, Kabbage, Square, and Paypal, and the largest seven banks in our sample: JPMorgan, Bank of America, Wells Fargo, U.S. Bank, Truist, PNC, and TD Bank. In each regression, the dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. The *Asian* indicator is defined to be 1 for restaurants that we identify as Asian food restaurants. The $Lender_j$ (*e,g.*, *Kabbage*) indicator is defined to be 1 for loans backed by that lender (e.g. by Kabbage). The omitted category is all other lenders. Control variables are the same as in Table 3 which contain lender dummies, racial group dummy, employment size, franchise dummy, month-city fixed effects, business type fixed effects, and eating policy dummies. Detailed variable definitions are in Appendix Table A1. Standard errors are clustered at the restaurant-lender level.

Table 1 Summary Statistics

Table 1.1 Restaurant and Lender Characteristics – Cross Section

	Panel A: 2020 PPP First Draw															
	Full Sample								Matched Sample							
	N	Mean	S.D.	Min	P.25	Median	P.75	Max	N	Mean	S.D.	Min	P.25	Median	P.75	Max
I(Minority)	92,557	0.32	0.46	0	0	0	1	1	86,097	0.33	0.47	0	0	0	1	1
I(African Ame.)		0.01	0.08	0	0	0	0	1		0.01	0.08	0	0	0	0	1
I(Asian)		0.18	0.39	0	0	0	0	1		0.20	0.40	0	0	0	0	1
I(Hispanic)		0.13	0.33	0	0	0	0	1		0.13	0.34	0	0	0	0	1
Employment		18.62	31.02	1	5	11	21	500		14.79	17.44	1	5	10	19	500
I(Franchise)		0.12	0.33	0	0	0	0	1		0.11	0.32	0	0	0	0	1
I(Fintech)		0.09	0.29	0	0	0	0	1		0.10	0.29	0	0	0	0	1
Δ(Date)		26.87	24.19	0	10	25	28	127		27.64	24.43	0	11	25	28	127
I(Rel.)		0.03	0.18	0	0	0	0	1		0.03	0.18	0	0	0	0	1
Rel. (N. Loans)		0.04	0.25	0	0	0	0	8		0.04	0.25	0	0	0	0	8
Rel. (A. Loan)		18	3,074	0	0	0	0	680,000		20	3,187	0	0	0	0	680,000
BC		52.08	96.02	1	8	23	59	3,655		50.98	91.22	1	8	23	58	3,655
GS_{zip}		4,236	5,079	1	220	1,295	8,979	16,637		4,362	5,140	1	225	1,354	10,684	16,637
GS_{city}		2,715	3,252	1	159	835	6,096	11,415		2,797	3,294	1	162	886	6,458	11,415
I(New Bank)	82,287	0.04	0.20	0	0	0	0	1	76,082	0.04	0.20	0	0	0	0	1
I(CU)	85,351	0.03	0.18	0	0	0	0	1	79,147	0.03	0.18	0	0	0	0	1
I(CD)	82,821	0.01	0.08	0	0	0	0	1	76,605	0.01	0.08	0	0	0	0	1

Table 1 Summary Statistics (Cont.)

Restaurant and Lender Characteristics – Cross Section (Cont.)

	Panel B: 2021 PPP First Draw															
	Full Sample								Matched Sample							
	N	Mean	S.D.	Min	P.25	Median	P.75	Max	N	Mean	S.D.	Min	P.25	Median	P.75	Max
I(Minority)	6,268	0.38	0.49	0	0	0	1	1	6,024	0.39	0.49	0	0	0	1	1
I(African Ame.)		0.01	0.11	0	0	0	0	1		0.01	0.12	0	0	0	0	1
I(Asian)		0.22	0.41	0	0	0	0	1		0.22	0.42	0	0	0	0	1
I(Hispanic)		0.15	0.36	0	0	0	0	1		0.16	0.36	0	0	0	0	1
Employment		9.39	13.41	1	3	6	11	342		8.41	8.66	1	3	6	10	93
I(Franchise)		0.06	0.23	0	0	0	0	1		0.06	0.23	0	0	0	0	1
I(Fintech)		0.17	0.38	0	0	0	0	1		0.18	0.38	0	0	0	0	1
Δ(Date)		41.12	21.14	0	23	39	60	78		41.01	21.05	0	23	39	60	78
I(Rel.)		0.02	0.13	0	0	0	0	1		0.02	0.13	0	0	0	0	1
Rel. (N. Loans)		0.02	0.16	0	0	0	0	3		0.02	0.15	0	0	0	0	3
Rel. (A. Loan)		0.00	0.06	0	0	0	0	3		0.00	0.06	0	0	0	0	3
BC		33.01	64.64	1	5	14	38	2,095		32.60	59.53	1	5	14	38	2,095
GS_{zip}		5,702	5,875	1	266	3,275	10,972	16,637		5,808	5,893	1	284	3,381	10,972	16,637
GS_{city}		3,707	3,872	1	188	2,200	6,595	11,415		3,775	3,885	1	195	2,225	6,595	11,415
I(New Bank)	4,866	0.04	0.20	0	0	0	0	1	4,648	0.04	0.20	0	0	0	0	1
I(CU)	4,962	0.02	0.14	0	0	0	0	1	4,741	0.02	0.14	0	0	0	0	1
I(CD)	5,299	0.05	0.21	0	0	0	0	1	5,080	0.05	0.21	0	0	0	0	1

Table 1.2 Restaurant Ratings – Restaurant-Level Panel

	Full Sample								Matched Sample							
	N	Mean	S.D.	Min	P.25	Median	P.75	Max	N	Mean	S.D.	Min	P.25	Median	P.75	Max
	Panel A: 2020 PPP First Draw															
	Before Covid-19															
Rating Stars	1,032,002	3.84	1.21	1	3	4	5	5	959,322	3.84	1.20	1	3	4	5	5
	During Covid-19															
Rating Stars	464,639	3.92	1.29	1	3	4	5	5	432,599	3.93	1.29	1	3	4	5	5
	Panel B: 2021 PPP First Draw															
	Before Covid-19															
Rating Stars	51,845	3.95	1.22	1	3	4	5	5	50,103	3.95	1.22	1	3	4	5	5
	During Covid-19															
Rating Stars	26,492	4.06	1.25	1	4	5	5	5	25,477	4.06	1.25	1	4	5	5	5

Table 2 Fintech Lenders and Minority-owned Businesses

This table reports the linear probability regression results where the dependent variable is the *Fintech* loan indicator (0/1). The key independent variables are *African American*, *Asian*, and *Hispanic* indicators that are defined to be 1 for restaurants with the corresponding food type. The 2020 and 2021 PPP waves are indicated in column heads. The matched sample is constructed by matching minority borrowers with non-minority borrowers in the same state, same business type (aggregated), same food price range, and of an employment size with a difference of at most five employees. In addition to the variables reported in the table, we also control for city and business type fixed effects. Detailed variable definitions are in Appendix Table A1. For demonstration purposes, the dependent variable is multiplied by 100. The sample is the linked restaurant-loan-level cross-sectional dataset. Standard errors are clustered at the city level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	*I*(Fintech) × 100							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African Ame.)	8.00***	4.99***	7.64***	4.86***	16.18***	5.52	16.07***	6.62
	(1.59)	(1.67)	(1.64)	(1.71)	(5.05)	(6.08)	(5.07)	(6.01)
I(Asian)	7.43***	6.07***	7.08***	5.84***	10.14***	6.10***	9.60***	5.67***
	(0.38)	(0.40)	(0.38)	(0.40)	(1.33)	(1.80)	(1.34)	(1.82)
I(Hispanic)	0.88***	0.06	0.82**	0.04	4.95***	3.31*	5.04***	3.71*
	(0.32)	(0.32)	(0.32)	(0.33)	(1.42)	(1.93)	(1.44)	(1.98)
Employment	-0.06***	-0.06***	-0.14***	-0.14***	-0.14***	-0.12***	-0.26***	-0.30***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.03)	(0.05)	(0.05)	(0.07)
I(Franchise)	-0.31	-0.23	0.02	-0.16	-2.95*	-7.72***	-2.42	-6.90**
	(0.32)	(0.34)	(0.36)	(0.38)	(1.78)	(2.74)	(1.88)	(2.85)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	92,556	88,873	86,095	82,426	6,266	4,150	6,022	3,984
Adjusted R^2	0.041	0.062	0.042	0.062	0.061	0.078	0.061	0.084

Table 3 Minority-Non-Minority Rating Gap

This table reports the regression results from examining the difference in ratings between minority- and non-minority-owned restaurants that borrow from fintech and non-fintech lenders. In Panels A and B, we report results on the 2020 and 2021 PPP waves, respectively. The dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The *Fintech* indicator is defined to be 1 for loans backed by fintech lenders. The matched sample is constructed by matching minority borrowers with non-minority borrowers in the same state, same business type (aggregated), same food price range, and of an employment size with a difference of at most five employees. In addition to the variables reported in the table, we also control for city × month (or month) fixed effects, business type fixed effects, and eating policy dummies for options of delivery, takeout, reservations, and outdoor seating. Detailed variable definitions are in Appendix Table A1. *Employment* is divided by 100 for demonstration purposes. The sample is the linked restaurant-loan monthly panel dataset where we calculate the monthly average of the ratings. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021. Standard errors are clustered at the restaurant level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw

Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.) × *I*(Fintech)	-0.11	-0.09	-0.11	-0.09	-0.25^{**}	-0.23^{**}	-0.24^{**}	-0.23^{**}
	(0.07)	(0.08)	(0.08)	(0.08)	(0.11)	(0.11)	(0.11)	(0.11)
I(Asian) × *I*(Fintech)	-0.08^{***}	-0.09^{***}	-0.08^{***}	-0.09^{***}	-0.06^{***}	-0.04^{*}	-0.06^{***}	-0.04^{*}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
I(Hisp.) × *I*(Fintech)	-0.01	0.01	-0.01	0.01	-0.02	0.00	-0.02	-0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
I(Fintech)	0.05^{***}	0.06^{***}	0.05^{***}	0.06^{***}	0.05^{***}	0.04^{***}	0.05^{***}	0.04^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
I(African Ame.)	0.12^{***}	0.15^{***}	0.11^{***}	0.14^{***}	0.05	0.06	0.04	0.05
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
I(Asian)	-0.09^{***}	-0.07^{***}	-0.09^{***}	-0.08^{***}	-0.03^{***}	-0.03^{***}	-0.04^{***}	-0.04^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
I(Hisp.)	-0.09^{***}	-0.09^{***}	-0.09^{***}	-0.09^{***}	-0.11^{***}	-0.11^{***}	-0.11^{***}	-0.11^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Employment	-0.12^{***}	-0.12^{***}	-0.22^{***}	-0.21^{***}	-0.11^{***}	-0.12^{***}	-0.19^{***}	-0.19^{***}
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
I(Franchise)	-0.89^{***}	-0.87^{***}	-0.88^{***}	-0.85^{***}	-1.06^{***}	-1.02^{***}	-1.05^{***}	-1.00^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Eating Policy Controls	X	X	X	X	X	X	X	X
Observations	1,032,002	974,781	959,322	902,934	464,639	434,948	432,598	403,363
Adjusted R^2	0.046	0.067	0.043	0.064	0.052	0.072	0.048	0.069

Table 3 Minority-Non-Minority Rating Gap (Cont.)

Panel B: 2021 PPP First Draw								
Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.) × *I*(Fintech)	-0.13	-0.31	-0.12	-0.30	-0.14	-0.29	-0.12	-0.26
	(0.17)	(0.20)	(0.17)	(0.21)	(0.18)	(0.21)	(0.18)	(0.21)
I(Asian) × *I*(Fintech)	0.02	0.08	0.03	0.10	-0.02	0.01	-0.00	0.03
	(0.06)	(0.09)	(0.06)	(0.09)	(0.07)	(0.10)	(0.07)	(0.10)
I(Hispanic) × *I*(Fintech)	0.08	0.13	0.08	0.13	-0.18**	-0.28**	-0.19**	-0.27**
	(0.07)	(0.11)	(0.07)	(0.11)	(0.09)	(0.13)	(0.09)	(0.13)
I(Fintech)	-0.06	-0.07	-0.07*	-0.08	-0.06	-0.01	-0.06	-0.02
	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)
I(African Ame.)	0.16	0.31**	0.15	0.31**	-0.05	-0.01	-0.05	-0.01
	(0.11)	(0.13)	(0.11)	(0.12)	(0.11)	(0.13)	(0.11)	(0.13)
I(Asian)	-0.13***	-0.13***	-0.14***	-0.14***	-0.04	-0.01	-0.04	-0.01
	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)
I(Hispanic)	-0.13***	-0.10**	-0.12***	-0.09*	-0.16***	-0.09*	-0.15***	-0.08
	(0.03)	(0.05)	(0.03)	(0.05)	(0.04)	(0.06)	(0.04)	(0.06)
Employment	-0.34***	-0.32**	-0.72***	-0.82***	-0.38***	-0.42**	-0.60***	-0.82***
	(0.10)	(0.15)	(0.11)	(0.18)	(0.10)	(0.18)	(0.12)	(0.19)
I(Franchise)	-0.91***	-0.84***	-0.88***	-0.79***	-0.91***	-0.81***	-0.90***	-0.77***
	(0.06)	(0.08)	(0.06)	(0.08)	(0.07)	(0.10)	(0.07)	(0.10)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Eating Policy Controls	X	X	X	X	X	X	X	X
Observations	51,844	29,256	50,102	28,211	26,491	14,723	25,476	14,095
Adjusted R^2	0.039	0.049	0.039	0.050	0.041	0.050	0.039	0.047

Table 4 Restaurant Ratings

This table reports the linear probability the regression results from examining the relationship between restaurant ratings and fintech/racial group indicators. The dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The *Fintech* indicator is defined to be 1 for loans backed by fintech lenders. The 2020 and 2021 PPP waves are indicated in column heads. In addition to the variables reported in the table, we also control for city × month (or month) fixed effects, business type fixed effects, and eating policy dummies for options of delivery, takeout, reservations, and outdoor seating. Detailed variable definitions are in Appendix Table A1. *Employment* is divided by 100 for demonstration purposes. The sample is the linked restaurant-loan monthly panel dataset where we calculate the monthly average of the ratings. Standard errors are clustered at the restaurant level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	Rating Stars					
Sample	2020 PPP	2021 PPP	2020 PPP	2021 PPP	2020 PPP	2021 PPP
	(1)	(2)	(3)	(4)	(5)	(6)
I(Fintech)	0.02***	-0.04				
	(0.01)	(0.04)				
I(Minority)					-0.07***	-0.08***
					(0.00)	(0.03)
I(African American)			0.10***	0.10		
			(0.03)	(0.10)		
I(Asian)			-0.07***	-0.08**		
			(0.01)	(0.03)		
I(Hispanic)			-0.09***	-0.10***		
			(0.01)	(0.04)		
Employment	-0.11***	-0.34**	-0.12***	-0.36**	-0.12***	-0.36**
	(0.01)	(0.15)	(0.01)	(0.15)	(0.01)	(0.15)
I(Franchise)	-0.89***	-0.81***	-0.91***	-0.83***	-0.91***	-0.83***
	(0.01)	(0.07)	(0.01)	(0.07)	(0.01)	(0.07)
City × Monthly FEs	Yes	Yes	Yes	Yes	Yes	Yes
Business Type FEs	Yes	Yes	Yes	Yes	Yes	Yes
Eating Policy Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,409,729	43,981	1,409,729	43,981	1,409,729	43,981
Adjusted R^2	0.069	0.049	0.070	0.050	0.069	0.050

Table 5 Previous Lending Relationships and Minority-owned Businesses

This table reports the regression results from examining the difference in previous lending relationships between minority- and non-minority-owned restaurants. In Panels A and B, we report results on the 2020 and 2021 PPP waves, respectively. The dependent variable in columns (1) and (2) is a dummy variable that equals 1 if the borrower had SBA 7(a) or 504 loans during 2009-2019. In columns (3) and (4), the dependent variable is the total number of SBA 7(a) or 504 loans during 2009-2019. In columns (5) and (6), the dependent variable is the value (in USD millions) of SBA 7(a) or 504 loans during 2009-2019. *A. Loan* is winsorized at the 1% and 99% cuts. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The construction of the matched sample and control variables are the same as in Table 2. Detailed variable definitions are in Appendix Table A1. For demonstration purposes, all dependent variables are multiplied by 100, and *Employment* is divided by 100. The sample is the linked restaurant-loan-level cross-sectional dataset. Standard errors are clustered at the city level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw						
Dep. Var.	*I*(Rel.) × 100		Rel. (N. Loans) × 100		Rel. (A. Loan) × 100	
	(1)	(2)	(3)	(4)	(5)	(6)
I(African Ame.)	-0.76	-0.87	-0.91	-1.20	-0.04	-0.21
	(0.66)	(0.68)	(1.09)	(1.13)	(0.33)	(0.34)
I(Asian)	-0.72***	-1.00***	-1.09***	-1.42***	-0.06	-0.23**
	(0.16)	(0.18)	(0.22)	(0.26)	(0.08)	(0.09)
I(Hispanic)	-1.11***	-1.03***	-1.60***	-1.40***	-0.25***	-0.30***
	(0.15)	(0.17)	(0.20)	(0.21)	(0.09)	(0.09)
Employment	2.34***	2.11***	3.56***	3.21***	2.99***	2.96***
	(0.43)	(0.45)	(0.59)	(0.61)	(0.32)	(0.34)
I(Franchise)	3.87***	3.83***	4.06***	3.98***	2.10***	1.99***
	(0.29)	(0.31)	(0.38)	(0.41)	(0.17)	(0.18)
City FEs		X		X		X
Business Type FEs	X	X	X	X	X	X
Observations	86,095	82,426	86,095	82,426	86,095	82,426
Adjusted R^2	0.011	0.008	0.009	0.004	0.011	-0.010
Panel B: 2021 PPP First Draw						
Dep. Var.	*I*(Rel.) × 100		Rel. (N. Loans) × 100		Rel. (A. Loan) × 100	
	(1)	(2)	(3)	(4)	(5)	(6)
I(African Ame.)	0.71	1.89	0.42	1.59	-0.24	-0.15
	(1.71)	(2.35)	(1.72)	(2.39)	(0.20)	(0.29)
I(Asian)	-0.47	-0.07	-0.70	-0.06	-0.23**	-0.36*
	(0.40)	(0.57)	(0.46)	(0.65)	(0.10)	(0.21)
I(Hispanic)	-0.69	-0.02	-0.90*	0.02	-0.23	-0.15
	(0.45)	(0.67)	(0.52)	(0.79)	(0.16)	(0.22)
Employment	3.40	4.95	3.63	5.63	2.94**	4.40**
	(2.13)	(3.34)	(2.58)	(4.36)	(1.16)	(2.10)
I(Franchise)	1.43	1.61	1.75	2.27	0.35	0.60
	(0.99)	(1.25)	(1.23)	(1.67)	(0.34)	(0.49)
City FEs		X		X		X
Business Type FEs	X	X	X	X	X	X
Observations	6,022	3,984	6,022	3,984	6,022	3,984
Adjusted R^2	0.005	-0.011	0.004	-0.028	0.003	-0.095

Table 6 Fintech Lenders and Previous Lending Relationships

This table reports the linear probability regression results where the dependent variable is the *Fintech* loan indicator (0/1). The key independent variables are *I(Rel.)*, a dummy variable that equals 1 if the borrower had SBA 7(a) or 504 loans during 2009-2019, *Rel. (N. Loans)*, the total number of SBA 7(a) or 504 loans borrowed during 2009-2019, and *Rel. (A. Loans)*, the value (in USD millions) of SBA 7(a) or 504 loans borrowed during 2009-2019. In panels A and B, we report results on the 2020 and 2021 PPP waves, respectively. *A. Loan* is winsorized at the 1% and 99% cuts. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The construction of the matched sample and control variables are the same as in Table 2. Detailed variable definitions are in Appendix Table A1. For demonstration purposes, the dependent variable is multiplied by 100. The sample is the linked restaurant-loan-level cross-sectional dataset. Standard errors are clustered at the city level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw						
Dep. Var.	*I*(Fintech) × 100					
	(1)	(2)	(3)	(4)	(5)	(6)
I(Rel.)	-5.76***	-5.31***				
	(0.48)	(0.53)				
Rel. (N. Loans)			-3.64***	-3.34***		
			(0.41)	(0.43)		
Rel. (A. Loan)					-4.60***	-4.96***
					(0.79)	(0.80)
Employment	-0.15***	-0.15***	-0.15***	-0.15***	-0.15***	-0.15***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
I(Franchise)	-1.14***	-1.10***	-1.22***	-1.17***	-1.28***	-1.22***
	(0.36)	(0.36)	(0.36)	(0.36)	(0.36)	(0.36)
City FEs		X		X		X
Business Type FEs	X	X	X	X	X	X
Observations	86,095	82,426	86,095	82,426	86,095	82,426
Adjusted R^2	0.035	0.058	0.035	0.058	0.034	0.057
Panel B: 2021 PPP First Draw						
Dep. Var.	*I*(Fintech) × 100					
	(1)	(2)	(3)	(4)	(5)	(6)
I(Rel.)	-15.60***	-10.38***				
	(0.81)	(1.97)				
Rel. (N. Loans)			-12.11***	-8.26***		
			(0.96)	(1.62)		
Rel. (A. Loan)					-16.66***	-11.31***
					(4.52)	(3.18)
Employment	-0.31***	-0.31***	-0.31***	-0.31***	-0.31***	-0.31***
	(0.05)	(0.07)	(0.05)	(0.07)	(0.05)	(0.07)
I(Franchise)	-4.20**	-8.26***	-4.21**	-8.24***	-4.37**	-8.35***
	(1.89)	(2.81)	(1.90)	(2.82)	(1.89)	(2.80)
City FEs		X		X		X
Business Type FEs	X	X	X	X	X	X
Observations	6,022	3,984	6,022	3,984	6,022	3,984
Adjusted R^2	0.052	0.083	0.052	0.082	0.050	0.082

Table 7 Business Capital

This table reports the regression results from examining the impact of business capital on the difference in the minority-non-minority rating gap between fintech and non fintech lenders. The 2020 and 2021 waves are indicated in column heads. The dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. Business capital (*BC*) is proxied by the total number of ratings in the entire period of our analysis (from April 2018 to March 2021). *BC* is divided by 100 for demonstration purposes and winsorized at the 99% cuts. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The *Fintech* indicator is defined to be 1 for loans backed by fintech lenders. The construction of the matched sample and control variables are the same as in Table 3. Detailed variable definitions are in Appendix Table A1. *Employment* is divided by 100 for demonstration purposes. The sample is the linked restaurant-loan monthly panel dataset where we calculate the monthly average of the ratings. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021.Standard errors are clustered at the restaurant level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	**Rating Stars**							
Sample	2020 PPP First Draw				2021 PPP First Draw			
	Before Covid-19		During Covid-19		Before Covid-19		During Covid-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.) × *I*(FT) × BC	0.07	0.07*	0.03	0.03	0.00	-0.07	-0.00	0.04
	(0.04)	(0.04)	(0.13)	(0.11)	(0.09)	(0.12)	(0.09)	(0.12)
I(Asia.) × *I*(FT) × BC	0.11***	0.10***	0.08***	0.07***	0.24***	0.28***	0.12***	0.17***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.05)	(0.04)	(0.05)
I(Hisp.) × *I*(FT) × BC	0.13***	0.12***	0.09***	0.08***	0.06	-0.00	-0.08	-0.18
	(0.02)	(0.02)	(0.02)	(0.02)	(0.06)	(0.09)	(0.08)	(0.11)
I(FT)	-0.02***	-0.01	-0.02	-0.01	-0.11***	-0.11**	-0.12***	-0.10*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.03)	(0.05)
I(African Ame.)	0.09***	0.13***	-0.00	0.01	0.11	0.25**	-0.08	-0.09
	(0.03)	(0.03)	(0.04)	(0.04)	(0.10)	(0.12)	(0.10)	(0.12)
I(Asian)	-0.11***	-0.10***	-0.05***	-0.05***	-0.17***	-0.16***	-0.06**	-0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)	(0.03)	(0.04)
I(Hispanic)	-0.10***	-0.10***	-0.12***	-0.11***	-0.11***	-0.06	-0.18***	-0.12**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.03)	(0.05)
Employment	-0.22***	-0.21***	-0.19***	-0.20***	-0.75***	-0.84***	-0.61***	-0.84***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.11)	(0.18)	(0.13)	(0.19)
I(Franchise)	-0.87***	-0.85***	-1.05***	-1.00***	-0.88***	-0.78***	-0.90***	-0.78***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.06)	(0.08)	(0.07)	(0.10)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	959,322	902,934	432,598	403,363	50,102	28,211	25,476	14,095
Adjusted R^2	0.044	0.064	0.049	0.069	0.041	0.053	0.040	0.048

Table 8 Relative Geographic Lending Scope

This table reports the regression results from examining the impact of geographic lending scope on the difference in the minority-non-minority rating gap between fintech and non fintech lenders. The 2020 and 2021 waves are indicated in column heads. The dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. Relative geographic lending scope (GS_r) is calculated as the total number of zip codes divided by the total number of cities that the lender covers in the entire PPP sample. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The *Fintech* indicator is defined to be 1 for loans backed by fintech lenders. The construction of the matched sample and control variables are the same as in Table 3. Detailed variable definitions are in Appendix Table A1. *Employment* is divided by 100 for demonstration purposes. The sample is the linked restaurant-loan monthly panel dataset where we calculate the monthly average of the ratings. CDFIs and CDCs are excluded because their lending scope may be restricted to certain communities. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021. Standard errors are clustered at the restaurant level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	**Rating Stars**							
Sample	2020 PPP First Draw				2021 PPP First Draw			
	Before Covid-19		During Covid-19		Before Covid-19		During Covid-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.)×I(FT)×GS_r	-0.07	-0.06	-0.15**	-0.15**	-0.07	-0.21	-0.07	-0.17
	(0.05)	(0.05)	(0.07)	(0.07)	(0.11)	(0.14)	(0.12)	(0.15)
I(Asian)×I(FT)×GS_r	-0.06***	-0.06***	-0.04***	-0.03**	0.02	0.06	-0.00	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.06)	(0.04)	(0.06)
I(Hisp.)×I(FT)×GS_r	-0.00	0.01	-0.01	-0.00	0.05	0.06	-0.12**	-0.18**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.07)	(0.06)	(0.09)
I(FT)	0.05***	0.06***	0.05***	0.04***	-0.07*	-0.07	-0.06	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.06)	(0.04)	(0.06)
I(African Ame.)	0.11***	0.14***	0.03	0.04	0.14	0.32**	-0.06	-0.02
	(0.03)	(0.03)	(0.04)	(0.04)	(0.11)	(0.13)	(0.12)	(0.14)
I(Asian)	-0.09***	-0.08***	-0.04***	-0.04***	-0.14***	-0.14***	-0.04	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.03)	(0.04)
I(Hispanic)	-0.09***	-0.09***	-0.11***	-0.11***	-0.12***	-0.08*	-0.15***	-0.09
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.05)	(0.04)	(0.06)
Employment	-0.21***	-0.21***	-0.19***	-0.19***	-0.71***	-0.83***	-0.60***	-0.81***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.11)	(0.18)	(0.13)	(0.19)
I(Franchise)	-0.88***	-0.86***	-1.05***	-1.00***	-0.88***	-0.77***	-0.90***	-0.77***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.06)	(0.08)	(0.07)	(0.10)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	952,731	896,408	429,480	400,262	49,403	27,632	25,036	13,745
Adjusted R^2	0.044	0.064	0.049	0.069	0.039	0.049	0.039	0.047

Table 9 First-Time Banks

This table reports the regression results of restaurants that borrow from lenders who are banks that participate in SBA programs for the first time and from lenders who had previously participated in SBA programs for the matched sample. We use the SBA 7(a) and 504 loan-level data from 1990-2019 to identify lenders that participated in SBA programs before. We exclude fintech lenders and non-banks. In Panel A, the dependent variable is the *New Bank* loan indicator (0/1) that equals one if the lender is a first-time bank in SBA programs. In Panel B, the dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. Other variable definitions, sample, the construction of the matched sample, and control variables are the same as in Table 2 (Panel A) and Table 3 (Panel B). Detailed variable definitions are in Appendix Table A1. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021. The sample is the linked restaurant-loan-level cross-sectional dataset (Panel A) and the linked restaurant-loan monthly panel dataset (Panel B). Standard errors are clustered at the city level (Panel A) and the restaurant level (Panel B), and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: First-Time Banks Usage

Dep. Var.	*I*(New Bank) × 100							
	2020 PPP				2021 PPP			
Sample	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African Ame.)	-0.63	0.20	-0.54	0.44	5.31	7.54	5.13	7.36
	(0.92)	(0.93)	(0.94)	(0.96)	(6.32)	(7.76)	(6.43)	(7.87)
I(Asian)	-2.23^{***}	-1.40^{***}	-2.21^{***}	-1.39^{***}	-2.54^{***}	-1.82^{**}	-2.48^{***}	-1.84^{**}
	(0.21)	(0.21)	(0.21)	(0.21)	(0.71)	(0.79)	(0.71)	(0.83)
I(Hispanic)	-0.40	-0.12	-0.45^{*}	-0.17	1.11	1.98	0.99	2.09
	(0.25)	(0.24)	(0.25)	(0.25)	(1.05)	(1.53)	(1.06)	(1.58)
Employment	-0.01^{***}	-0.01^{***}	-0.00	0.00	0.01	-0.01	0.03	-0.02
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.04)	(0.04)
I(Franchise)	-0.42	-0.07	-0.35	-0.09	-1.13	0.77	-1.26	0.60
	(0.26)	(0.27)	(0.29)	(0.30)	(1.07)	(1.67)	(1.13)	(1.78)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	82,285	78,589	76,080	72,390	4,865	2,950	4,647	2,815
Adjusted R^2	0.002	0.132	0.002	0.133	0.005	0.098	0.004	0.094

Panel B: Rating Gap

Dep. Var.	**Rating Stars**							
Sample	2020 PPP				2021 PPP			
	Before Covid-19		During Covid-19		Before Covid-19		During Covid-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.) × *I*(New Bank)	-0.08	-0.07	0.09	0.05	0.66^{***}	0.42^{*}	0.41^{*}	0.31
	(0.13)	(0.16)	(0.14)	(0.19)	(0.15)	(0.24)	(0.24)	(0.31)
I(Asian) × *I*(New Bank)	-0.05	-0.02	-0.02	-0.02	0.28^{*}	0.18	-0.09	0.07
	(0.04)	(0.04)	(0.04)	(0.05)	(0.15)	(0.30)	(0.16)	(0.37)
I(Hisp.) × *I*(New Bank)	0.00	0.01	0.02	0.01	-0.09	-0.27	-0.28	-0.37
	(0.04)	(0.04)	(0.04)	(0.05)	(0.13)	(0.22)	(0.18)	(0.33)
I(New Bank)	0.04^{**}	0.03	0.00	0.01	-0.04	0.13	0.22^{***}	0.27^{*}
	(0.01)	(0.02)	(0.02)	(0.02)	(0.08)	(0.17)	(0.07)	(0.14)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	845,747	789,355	380,498	351,392	38,183	19,342	19,275	9,592
Adjusted R^2	0.044	0.066	0.049	0.069	0.041	0.057	0.040	0.049

Table 10 Credit Unions

This table reports the regression results of restaurants that borrow from credit unions and from other lenders in the FFIEC list for the matched sample. We only include lenders that can be matched with THE FFIEC lender list. In panel A, the dependent variable is the *CU* loan indicator (0/1) that equals one if the lender is a credit union. In panel B, the dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. Other variable definitions, sample, the construction of the matched sample, and control variables are the same as in Table 2 (Panel A) and Table 3 (Panel B). Detailed variable definitions are in Appendix Table A1. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021. The sample is the linked restaurant-loan-level cross-sectional dataset (Panel A) and the linked restaurant-loan monthly panel dataset (Panel B). Standard errors are clustered at the city level (Panel A) and the restaurant level (Panel B), and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Credit Unions Usage

Dep. Var.	I(CU) × 100							
	2020 PPP				2021 PPP			
Sample	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African Ame.)	1.87*	2.39**	1.90*	2.50**	6.48	7.42	6.10	7.09
	(1.02)	(1.02)	(1.05)	(1.04)	(5.75)	(6.55)	(5.70)	(6.57)
I(Asian)	-1.47***	-1.50***	-1.49***	-1.57***	-2.06***	-2.68***	-2.18***	-2.79***
	(0.17)	(0.21)	(0.17)	(0.21)	(0.71)	(0.87)	(0.72)	(0.90)
I(Hispanic)	0.15	0.51**	0.21	0.53**	-0.73	0.03	-0.87	0.28
	(0.27)	(0.25)	(0.27)	(0.26)	(0.94)	(1.34)	(0.94)	(1.35)
Employment	-0.02***	-0.02***	-0.03***	-0.03***	-0.03	-0.04	-0.08**	-0.13***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.03)	(0.03)	(0.05)
I(Franchise)	-1.09***	-0.83***	-1.08***	-0.80***	-1.22	1.28	-1.45	1.08
	(0.19)	(0.20)	(0.20)	(0.21)	(1.12)	(1.72)	(1.11)	(1.75)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	85,349	81,702	79,145	75,502	5,298	3,321	5,079	3,184
Adjusted R^2	0.004	0.099	0.004	0.098	0.004	0.069	0.008	0.083

Panel B: Rating Gap

Dep. Var.	**Rating Stars**							
Sample	2020 PPP				2021 PPP			
	Before Covid-19		During Covid-19		Before Covid-19		During Covid-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African Ame.)× I(CU)	-0.06	-0.07	-0.12	0.04	0.67***	0.54***	0.50**	0.70**
	(0.11)	(0.12)	(0.18)	(0.16)	(0.13)	(0.20)	(0.20)	(0.28)
I(Asian) × I(CU)	-0.04	-0.04	-0.12***	-0.11**	0.12	-0.12	0.00	0.17
	(0.04)	(0.04)	(0.04)	(0.05)	(0.11)	(0.17)	(0.13)	(0.24)
I(Hispanic) × I(CU)	-0.00	0.01	0.00	0.01	-0.11	-0.26	-0.01	0.29
	(0.04)	(0.04)	(0.04)	(0.05)	(0.15)	(0.18)	(0.15)	(0.27)
I(CU)	0.10***	0.10***	0.11***	0.11***	0.04	0.12	0.10	-0.18
	(0.01)	(0.02)	(0.02)	(0.02)	(0.06)	(0.10)	(0.07)	(0.14)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	882,486	826,845	396,912	368,112	41,716	21,715	20,931	10,694
Adjusted R^2	0.044	0.065	0.049	0.069	0.040	0.049	0.038	0.037

Table 11 CDFIs/CDCs

This table reports the regression results of restaurants that borrowed from community development oriented lenders and from banks for the matched sample. We exclude fintech lenders and other non-banks. In Panel A, the dependent variable is the *CDC* loan indicator (0/1) that equals one if the lender is a CDFI or CDC. In Panel B, the dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. Other variable definitions, sample, the construction of the matched sample, and control variables are the same as in Table 2 (Panel A) and Table 3 (Panel B). Detailed variable definitions are in Appendix Table A1. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021. The sample is the linked restaurant-loan-level cross-sectional dataset (Panel A) and the linked restaurant-loan monthly panel dataset (Panel B). Standard errors are clustered at the city level (Panel A) and the restaurant level (Panel B), and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: CDFIs/CDCs Usage

Dep. Var.	I(CDC) × 100							
Sample	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African Ame.)	2.37***	2.27***	2.38***	2.33***	5.74	3.25	5.84	3.34
	(0.77)	(0.81)	(0.79)	(0.83)	(3.70)	(3.82)	(3.76)	(3.88)
I(Asian)	0.32***	0.15	0.29***	0.11	-0.50	-1.76**	-0.60	-2.07***
	(0.09)	(0.10)	(0.09)	(0.10)	(0.44)	(0.73)	(0.46)	(0.74)
I(Hispanic)	0.65***	0.53***	0.66***	0.55***	0.53	-0.74	0.41	-0.87
	(0.16)	(0.17)	(0.16)	(0.18)	(0.67)	(0.87)	(0.62)	(0.83)
Employment	-0.01***	-0.01***	-0.01***	-0.01***	-0.01	-0.02	-0.04**	-0.06*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.02)	(0.02)	(0.03)
I(Franchise)	-0.15**	-0.05	-0.14*	-0.04	-0.60	-2.53**	-0.44	-2.53**
	(0.07)	(0.08)	(0.08)	(0.08)	(0.83)	(1.22)	(0.88)	(1.07)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	82,819	79,121	76,603	72,910	4,961	3,033	4,740	2,890
Adjusted R^2	0.002	-0.013	0.002	-0.016	0.003	0.015	0.003	0.006

Panel B: Rating Gap

Dep. Var.	**Rating Stars**							
Sample	2020 PPP				2021 PPP			
	Before Covid-19		During Covid-19		Before Covid-19		During Covid-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri. Ame.)× I(CDC)	-0.05	-0.03	0.05	-0.01	0.06	-0.23	0.26	0.23
	(0.11)	(0.12)	(0.15)	(0.17)	(0.20)	(0.31)	(0.28)	(0.35)
I(Asian) × I(CDC)	-0.23***	-0.20***	-0.07	-0.09	0.09	0.15	-0.25	-0.18
	(0.07)	(0.07)	(0.08)	(0.09)	(0.11)	(0.21)	(0.19)	(0.28)
I(Hispanic) × I(CDC)	-0.06	0.04	0.05	0.11	0.01	0.06	-0.03	0.45
	(0.07)	(0.08)	(0.09)	(0.10)	(0.15)	(0.31)	(0.20)	(0.28)
I(CDC)	0.20***	0.16***	0.07	0.04	0.09	0.11	0.12	0.03
	(0.04)	(0.04)	(0.05)	(0.06)	(0.09)	(0.13)	(0.08)	(0.12)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	852,090	795,599	383,485	354,350	38,882	19,848	19,715	9,915
Adjusted R^2	0.044	0.065	0.048	0.069	0.041	0.058	0.039	0.049

Table 12 Approval Date

This table reports the regression results from examining the difference in PPP loan approval dates between minority- and non-minority-owned restaurants that borrow from fintech and non-fintech lenders. The dependent variable, *Δ(Approval Date-PPP Starting Date)*, is the difference between PPP loan approval date and PPP starting date. The starting date is April 03, 2020 for the 2020 wave and Jan 12, 2021 for the 2021 wave. The 2020 and 2021 waves are indicated in column heads. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The *Fintech* indicator is defined to be 1 for loans backed by fintech lenders. The construction of the matched sample and control variables are the same as in Table 2. Detailed variable definitions are in Appendix Table A1. The sample is the linked restaurant-loan-level cross-sectional dataset. Standard errors are clustered at the city level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	Δ(Approval Date-PPP Starting Date)							
Sample	2020 PPP First Draw				2021 PPP First Draw			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.) × *I*(Fintech)	-3.30	-2.20	-3.12	-2.01	-3.61	-0.01	-3.82	-0.04
	(3.10)	(3.25)	(3.10)	(3.26)	(4.13)	(4.65)	(4.14)	(4.69)
I(Asian) × *I*(Fintech)	2.23***	3.11***	2.52***	3.39***	-8.11***	-7.34***	-8.20***	-7.54***
	(0.74)	(0.76)	(0.74)	(0.77)	(1.57)	(2.16)	(1.58)	(2.17)
I(Hispanic) × *I*(Fintech)	0.80	0.06	0.83	0.11	-8.72***	-6.71**	-8.75***	-6.83**
	(1.12)	(1.15)	(1.11)	(1.15)	(2.04)	(2.64)	(2.06)	(2.68)
I(Fintech)	14.31***	11.93***	13.63***	11.27***	2.42**	0.66	2.38**	0.50
	(0.47)	(0.52)	(0.48)	(0.52)	(0.94)	(1.28)	(0.96)	(1.30)
I(African Ame.)	9.63***	7.61***	8.88***	6.86***	8.71***	4.35	8.91***	4.56
	(1.23)	(1.29)	(1.24)	(1.29)	(2.65)	(2.98)	(2.72)	(3.06)
I(Asian)	10.37***	9.08***	9.72***	8.47***	2.43***	1.42	2.29***	1.28
	(0.32)	(0.33)	(0.31)	(0.33)	(0.77)	(1.09)	(0.78)	(1.10)
I(Hispanic)	5.47***	4.98***	5.30***	4.84***	3.15***	2.51*	3.18***	2.50*
	(0.28)	(0.28)	(0.28)	(0.29)	(0.89)	(1.30)	(0.90)	(1.33)
Employment	-0.09***	-0.09***	-0.20***	-0.19***	-0.05**	-0.05	-0.12***	-0.14***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.04)	(0.03)	(0.04)
I(Franchise)	-8.15***	-7.91***	-7.93***	-7.89***	1.21	0.92	1.62	1.84
	(0.20)	(0.21)	(0.22)	(0.23)	(1.14)	(1.59)	(1.19)	(1.61)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	92,556	88,873	86,095	82,426	6,266	4,150	6,022	3,984
Adjusted R^2	0.140	0.176	0.142	0.176	0.030	0.036	0.019	0.025

Appendix

Table A1 Variable Definition

Variable Name	Definition	Data Source
I(Fintech)	1 if the lender of the loan is a fintech lender, 0 otherwise	• PPP loan-level dataset • Consolidated fintech company list
I(Minority) *I*(African Ame.) *I*(Asian) *I*(Hispanic)	1 if the restaurant is of minority food type, 0 otherwise 1 if the restaurant is of African American food type, 0 otherwise 1 if the restaurant is of Asian food type (including Pacific Islander), 0 otherwise 1 if the restaurant is of Hispanic food type, 0 otherwise *When multiple food categories, African American ≳ Asian ≳ Hispanic.*	• yelp.com • Food type classification list
Rating Stars Eating Policy Food Price BC	Mean of all the customer ratings in the month which range from 0 to 5 Dummies for the following restaurant amenities: delivery, takeout, reservations, and outdoor seating Dummies for $,$$,$$$,$$$$ Business capital: the total number of ratings in the entire period of our analysis (from April 2018 to March 2021)	• yelp.com
Δ(Approval Date-PPP Starting Date) Employment *I*(Franchise) Business Type FEs Approval Date FEs GS_{zip} GS_{city}	Number of days between the date approved and April 3rd, 2020 for the 2020 PPP number of days between the date approved and Jan 12th, 2021 for the 2021 PPP *Jobs Reported* in the SBA original dataset 1 if the *Franchise Name* in the SBA original dataset is non-empty after our adjustments (see Online Appendix C3) Dummies based Business yype in the SBA original dataset, including the types of : Cooperative Corporation, Employee Stock Ownership Plan(ESOP), Independent Contractors, Joint Venture, Limited Liability Company(LLC), Limited Liability Partnership, Partnership, Professional Association, Qualified Joint-Venture (spouses), Self-Employed Individuals, Single Member LLC, Sole Proprietorship, Subchapter S Corporation, Tenant in Common, Tribal Concerns, Trust Dummies for the approval date in the SBA original dataset the total number of zip codes that the lender covers in the entire PPP loan sample The total number of cities that the lender covers in the entire PPP loan sample	• PPP loan-level dataset
City FEs	Dummies for cities Convert zip code in the SBA original dataset to city using the HUD-USPS ZIP Code Crosswalk data. If the zip code-city conversion is not available in the HUD data, we manually searched and find the city in the format in the HUD data. *We do not directly use the city information in the PPP data due to quality concerns.*	• PPP loan-level dataset • HUD User
New Bank	1 if the lender is a first-time bank, 0 otherwise (fintech lenders and non-banks are excluded) To identify whether the bank previously participated in the SBA programs, we use a combination of code-based and manual checks of lender name matching with the SBA 7(a) and 504 loan-level data from 1990-2019.	• PPP loan-level dataset • SBA 7(a) and 504 loan-level dataset (1990-2019)

Table A1 Variable Definition (Cont.)

CD	1 if the lender is a CDFI or CDC, 0 otherwise (fintech lenders and other non-banks are excluded)	• cdfifund.gov • SBA 504 (1990-2019)
Uninsured S&L CU	1 if the lender is not federally insured, 0 otherwise 1 if the lender is a Savings & Loan Association, 0 otherwise 1 if the lender is a Credit Union, 0 otherwise	• FFEIC *Missing if not matched with FFEIC*
I(Rel.) Rel. (N. Loans) Rel. (A. Loan)	1 if the borrower previously borrowed a SBA 7(a) or 504 loan Total number of SBA 7(a) and 504 loans the borrower has Total dollar value of SBA 7(a) and 504 loans the borrower has (million USD)	SBA 7(a) and 504 loan-level dataset (2009-2019)

Table A2 The List of Fintech Lenders in the First Draw of the PPP Program

Pair #	Servicing Lender	Originating Lender	N. Our	Our/722	N. 722	N. All
1	Cross River Bank	Cross River Bank	2165	26%	8440	324588
2	Cross River Bank Kabbage, Inc.	Kabbage, Inc.	1828	23%	7859	159823
3	Square Capital, LLC	Square Capital, LLC Celtic Bank Corporation	1521	22%	6966	86109
4	WebBank	WebBank	1415	31%	4639	82997
5	First Home Bank Loan Source Incorporated	Loan Source Incorporated some bank[35]	1019	28%	3654	36515
6	Itria Ventures LLC	Itria Ventures LLC	499	4%	12106	197238
7	Customers Bank Readycap Lending, LLC	Readycap Lending, LLC	413	13%	3301	67836
8	FC Marketplace, LLC (dba Funding Circle) Quontic Bank	FC Marketplace, LLC (dba Funding Circle)	187	25%	747	9738
9	Celtic Bank Corporation	Celtic Bank Corporation	155	30%	521	65376
10	Fundbox, Inc.	Fundbox, Inc.	119	23%	511	13454
11	Sunrise Banks, National Association	Sunrise Banks, National Association	69	32%	216	2200
12	BSD Capital, LLC dba Lendistry	BSD Capital, LLC dba Lendistry	67	23%	295	4814
13	Intuit Financing Inc. Quontic Bank	Intuit Financing Inc.	48	33%	145	17792
14	Opportunity Fund Community Development	Opportunity Fund Community Development	16	24%	67	1162
15	FinWise Bank	FinWise Bank	16	35%	46	693

[35] Loan Source shown in the PPP loan-level dataset to have the following 37 originators in the 2020-PPP round: Columbia Community CU, First State Bank, Renaissance Community Loan Fund, Inc., The Bryn Mawr Trust Company, Neighbors FCU, Ascend FCU, FirstBank, BNC National Bank, Pelican State CU, First Reliance Bank, Nano Banc, Pacific Premier Bank, Signature Bank of Georgia, The Hicksville Bank, Florida Capital Bank, National Association, Flagstar Bank, FSB, First Bank of Alabama, Stearns Bank National Association, Sterling National Bank, Bethpage FCU, Marlin Business Bank, KeyPoint CU, BCB Community Bank, Kearny Bank, Five Star Bank, Community Bank and Trust Company, Investors Bank, Peapack-Gladstone Bank, OceanFirst Bank, National Association, Financial Partners CU, Prudential Bank, Gather FCU, Northeast Bank, Southern First Bank, Malvern Bank, National Association, Orange County's CU, Neighborhood National Bank.

A Short Description on the Paycheck Protection Program

The Paycheck Protection Program (PPP) is a Small Business Administration (SBA) loan program established on April 3, 2020 as a temporary addition to the existing 7(a) loan program, in accordance with the Coronavirus Aid, Relief, and Economic Security Act (CARES Act) passed on March 27, 2020. The intent of the PPP is to provide small businesses with funds to maintain payroll costs and cover overheads during the Covid-19 crisis.

The first tranche of the 2020 PPP loans started on April 3, 2020. Until April 16, 2020, the initial allocation of $349 billion authorized by Congress was exhausted. The distribution of the second tranche of the PPP started on April 27 after Congress added additional funding to the program. The initial application deadline for the PPP loans was June 30, 2020 and later extended to August 8, 2020. As of August 8, 2020, in total $525 billion PPP loans were distributed, and $134 billion remained available. In total, $659 billion funds were authorized to the PPP by Public Law 116-147 in 2020.

The Economic Aid to Hard-Hit Small Businesses, Nonprofits, and Venues Act (Economic Aid Act) restarted the issuance of PPP loans in January 2021. The Act added $284 billion funding for PPP loans. The initial deadline of applying for PPP loans is March 31, 2021, later extended to May 31. The 2021 PPP program consists of a first draw for whom have not received a PPP loan before and a second draw for previous PPP recipients in 2020. Moreover, in 2021, the SBA undertook several steps to facilitate lending to minority borrowers, including encourage minority owned lenders to become PPP lenders.

For most industries, the eligibility requirement is either meeting the SBA size standards for small business or less than 500 employees. For the industries with a NAICS code that begins with 72 (Accommodations and Food Services), the business is eligible for the PPP as long as the number of employees is fewer than 500 at each location.

The PPP loans should generally be used for payroll costs and for mortgage interest, rent, utilities, and other worker protection related cost and the interest rate is fixed at 1%. The maturity of the loans issued before June 5, 2020 is two years and five years for loans issued after June 5. The principal of the PPP loan can be partially or fully forgiven conditioning on the loan spending on business maintaining and employee rehiring and maintaining. There is no collateral or personal guarantees requirement. Each loan is 100% guaranteed by the SBA.

Fintech played a crucial role in the distribution of PPP loans. Because of the large amount of loan demand, the goal of providing immediate assistance to borrowers, and the social-distancing requirement during the pandemic, the SBA allowed for a few non-traditional lenders specializing in fintech services to become eligible lenders, in addition to the SBA 7(a) lender, federally insured depository institution or credit union. Examples of fintech lenders in the PPP are Lendio, Paypal, Biz2credit, Kabbage, and Square.

This is the first large scale experiment of including fintech lenders in SBA programs. Most of the fintech companies are not participants in the SBA 7(a) or 504 programs before the Covid-19 crisis and therefore not PPP eligible lenders by default. At the very early stage of the PPP program in 2020, non-depository institutions including fintech companies were not able to operate similarly to depository institutions. On April 8, five days after the beginning of issuing PPP loans, the Federal Reserve Board authorized each regional Federal Reserve Banks to establish the Paycheck Protection Program Liquidity Facility (PPPLP), to provide liquidity to credit market by extending non-recourse credit to PPP lenders and taking PPP loans as collateral. The PPPLF became fully functional on April 16, but only eligible to depository institutions. On April 30, the PPPLP was extended to all PPP lenders approved by the SBA, including fintech companies.

Compare the Racial Group Measures PPP vs Yelp.com

Table A3 The List of Fintech Lenders in the First Draw of the PPP Program

This table reports the relationship between the racial group classification using information from PPP data and Yelp data. Panel A reports the share of each racial group based on information in the PPP loan-level data for each racial group using food type information from yelp.com. Rows indicate the racial group of the restaurant owners in the PPP dataset. Columns indicate the racial group of the restaurant using food type information from yelp.com. For example, the first row of the third column reports that 26.9% of restaurants that are classified as Hispanic based on information from yelp.com are classified as White based on PPP information. Panel B reports the parallel results of shares of Yelp racial groups for each PPP racial groups. Panel C reports the pairwise correlations between PPP race classifications and yelp race classifications. The sample includes all restaurant borrowers which have a valid yelp link and non-missing race and ethnicity information in the PPP dataset.

Panel A: Cross Shares – Compare Yelp with PPP

	Yelp				
PPP	White	Non-White	Hispanic	African Ame.	Asian
White	74.9%	12.2%	26.9%	12.0%	4.7%
Non-White	25.1%	87.8%	73.1%	88.0%	95.3%
Hispanic	3.9%	18.3%	51.9%	1.8%	1.8%
African Ame.	4.0%	5.2%	7.5%	80.1%	0.5%
Asian	13.7%	59.5%	5.9%	1.8%	89.6%
Native Ame.	3.5%	4.8%	7.8%	4.2%	3.4%
Observations	13,327	5,498	1,806	166	3,526

Panel B: Cross Shares – Compare PPP with Yelp

	PPP					
Yelp	White	Non-White	Hispanic	African Ame.	Asian	Native Ame.
White	93.7%	40.9%	34.2%	65.0%	35.8%	63.6%
Non-White	6.3%	59.1%	65.8%	35.0%	64.2%	36.4%
Hispanic	4.6%	16.2%	61.5%	16.4%	2.1%	19.3%
African Ame.	0.2%	1.8%	0.2%	16.2%	0.1%	1.0%
Asian	1.6%	41.1%	4.1%	2.3%	62.0%	16.2%
Observations	10,657	8,168	1,525	821	5,092	730

Panel C: Pairwise Correlation

	(1) Minority Yelp	(2) African Yelp	(3) Asian Yelp	(4) Hispanic Yelp
Minority PPP	0.58^{***}			
	(0.00)			
African PPP		0.35^{***}		
		(0.00)		
Asian PPP			0.52^{***}	
			(0.00)	
Hispanic PPP				0.68^{***}
				(0.00)
Observations	18,825			

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Proof of Proposition 1

Setting the outside option of borrowers to zero, the equilibrium in the race-biased tech-preference case is given by $(\underline{\gamma_{mf}}, \underline{\gamma_{mb}}, \underline{\gamma_{nf}}, \underline{\gamma_{nb}}, p_{mf}, p_{mb}, p_{nf}, p_{nb})$ that are determined by

$$M^m \int_{\underline{\gamma_{mf}}}^{\infty} f(x, \mu^m, \sigma^m) dx + M^n \int_{\underline{\gamma_{nf}}}^{\infty} f(x, \mu^n, \sigma^n) dx = M^f \quad (A.1)$$

$$M^m \int_{\underline{\gamma_{mb}}}^{\underline{\gamma_{mf}}} f(x, \mu^m, \sigma^m) dx + M^n \int_{\underline{\gamma_{nb}}}^{\underline{\gamma_{nf}}} f(x, \mu^n, \sigma^n) dx = M^b \quad (A.2)$$

$$\underline{\gamma_{mf}}(1 + \theta^m) - p_{mf} = \underline{\gamma_{mf}} - p_{mb} \quad (A.3)$$

$$\underline{\gamma_{nf}}(1 + \theta^n) - p_{nf} = \underline{\gamma_{nf}} - p_{nb} \quad (A.4)$$

$$\underline{\gamma_{mb}} - p_{mb} = 0 \quad (A.5)$$

$$\underline{\gamma_{nb}} - p_{nb} = 0 \quad (A.6)$$

$$p_{mf} = p_{nf} \quad (A.7)$$

$$p_{mb} = p_{nb} \quad (A.8)$$

$(A.3)$ to $(A.6)$ are the incentive compatibility constraints for the marginal borrower in the minority-fintech, non-minority-fintech, minority-bank, and non-minority-bank matches respectively.

$(A.7)$ and $(A.8)$ are the lender's incentive compatibility.

$$(A.5) + (A.6) + (A.8) \Rightarrow \underline{\gamma_{mb}} = \underline{\gamma_{nb}} \quad (A.9)$$

$$(A.3) + (A.4) + (A.7) \Rightarrow \underline{\gamma_{mf}}\theta^m = \underline{\gamma_{nf}}\theta^n \quad (A.10)$$

■

Proof of Corollary 1

The minority-non-minority rating gap in matching thresholds between fintech lenders and banks is,

$$(A.9) + \ (A.10) \Rightarrow \underline{\Delta\Delta} \stackrel{\text{def}}{=} \left(\underline{\gamma_{mf}} - \underline{\gamma_{nf}}\right) - \left(\underline{\gamma_{mb}} - \underline{\gamma_{nb}}\right) = \underline{\gamma_{mf}} - \underline{\gamma_{nf}}$$

$$= \frac{\underline{\underline{\gamma_{mf}}}}{\theta^n}(\theta^n - \theta^m) < 0 \ if \ \theta^m > \theta^n$$

In addition, minority-non-minority gap in the conditional expectation of the rating level between fintech lenders and banks is,

$$\mathbb{E}(\Delta\Delta|\cdot) \stackrel{\text{def}}{=} \left[\mathbb{E}\left(x \middle| x \geq \underline{\gamma_{mf}}, \mu^m, \sigma^m\right) - \mathbb{E}\left(x \middle| x \geq \underline{\gamma_{nf}}, \mu^n, \sigma^n\right)\right] - \left[\mathbb{E}\left(x \middle| \underline{\gamma_{mb}} \leq x < \underline{\gamma_{mf}}, \mu^m, \sigma^m\right) - \mathbb{E}\left(x \middle| \underline{\gamma_{nb}} \leq x < \underline{\gamma_{nf}}, \mu^n, \sigma^n\right)\right]$$

$$= \left[\mu^m + \sigma^m \frac{\varphi(\frac{\underline{\gamma_{mf}} - \mu^m}{\sigma^m})}{1 - \Phi(\frac{\underline{\gamma_{mf}} - \mu^m}{\sigma^m})} - \sigma^n \frac{\varphi\left(\frac{\underline{\gamma_{nf}} - \mu^n}{\sigma^n}\right)}{1 - \Phi(\frac{\underline{\gamma_{nf}} - \mu^n}{\sigma^n})}) - \mu^n\right] - \left[\mu^m + \sigma^m \frac{\varphi\left(\frac{\underline{\gamma_{mb}} - \mu^m}{\sigma^m}\right) - \sigma^m \varphi\left(\frac{\underline{\gamma_{mf}} - \mu^m}{\sigma^m}\right)}{\Phi\left(\frac{\underline{\gamma_{mf}} - \mu^m}{\sigma^m}\right) - \Phi\left(\frac{\underline{\gamma_{mb}} - \mu^m}{\sigma^m}\right)} - \sigma^n \frac{\varphi\left(\frac{\underline{\gamma_{nb}} - \mu^n}{\sigma^n}\right) - \varphi\left(\frac{\underline{\gamma_{nf}} - \mu^n}{\sigma^n}\right)}{\Phi\left(\frac{\underline{\gamma_{nf}} - \mu^n}{\sigma^n}\right) - \Phi\left(\frac{\underline{\gamma_{nb}} - \mu^n}{\sigma^n}\right)} - \mu^n\right]$$

$$= \sigma^m \left[\frac{\varphi(\frac{\underline{\gamma_{mf}} - \mu^m}{\sigma^m})}{1 - \Phi(\frac{\underline{\gamma_{mf}} - \mu^m}{\sigma^m})} - \frac{\varphi\left(\frac{\underline{\gamma_{mb}} - \mu^m}{\sigma^m}\right) - \varphi\left(\frac{\underline{\gamma_{mf}} - \mu^m}{\sigma^m}\right)}{\Phi\left(\frac{\underline{\gamma_{mf}} - \mu^m}{\sigma^m}\right) - \Phi\left(\frac{\underline{\gamma_{mb}} - \mu^m}{\sigma^m}\right)}\right] - \sigma^n \left[\frac{\varphi\left(\frac{\underline{\gamma_{nf}} - \mu^n}{\sigma^n}\right)}{1 - \Phi(\frac{\underline{\gamma_{nf}} - \mu^n}{\sigma^n})} - \frac{\varphi\left(\frac{\underline{\gamma_{nb}} - \mu^n}{\sigma^n}\right) - \varphi\left(\frac{\underline{\gamma_{nf}} - \mu^n}{\sigma^n}\right)}{\Phi\left(\frac{\underline{\gamma_{nf}} - \mu^n}{\sigma^n}\right) - \Phi\left(\frac{\underline{\gamma_{nb}} - \mu^n}{\sigma^n}\right)}\right] \text{(A.11)}$$

Where $\varphi(\cdot)$ and $\Phi(\cdot)$ are the density and cumulative distribution function of the standard normal distribution respectively.

Suppose that the underlying distribution is the same for minority and non-minority borrowers, i.e., $\mu^m = \mu^n = \mu$ and $\sigma^m = \sigma^n = \sigma$, combined with $(A.9)$ $\underline{\gamma_{mb}} = \underline{\gamma_{nb}} = \sigma\tilde{\gamma} + \mu$, (A.11) becomes,

$\sigma\left(G\left(\frac{\underline{\gamma_{mf}} - \mu}{\sigma}\right) - G\left(\frac{\underline{\gamma_{nf}} - \mu}{\sigma}\right)\right)$, where $G(x) = \frac{\varphi(x)}{1 - \Phi(x)} - \frac{\varphi(\tilde{\gamma}) - \varphi(x)}{\Phi(x) - \Phi(\tilde{\gamma})}$.

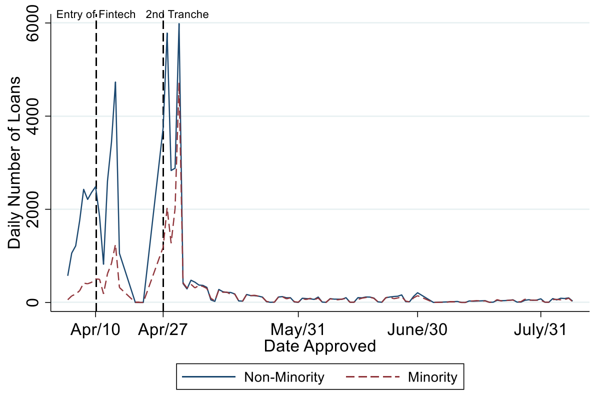
Using the symmetricity of normal distribution, $G(x) = \frac{\varphi(x)}{1 - \Phi(x)} - \frac{\varphi(\tilde{\gamma}) - \varphi(x)}{\Phi(x) - \Phi(\tilde{\gamma})} = \frac{\varphi(x)}{\Phi(-x)} + \frac{\varphi(x) - \varphi(\tilde{\gamma})}{\Phi(x) - \Phi(\tilde{\gamma})}$

■

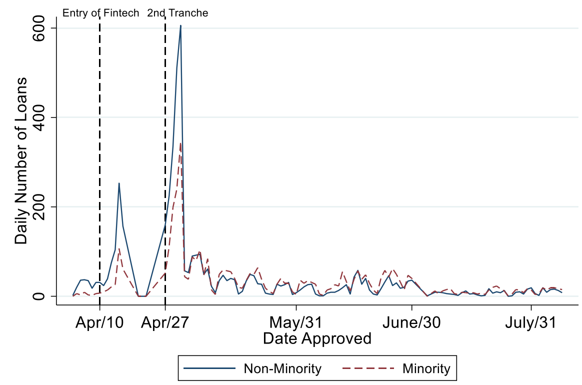
Online Appendix for “Fintech and Racial Barriers in Small Business Lending”

Contents

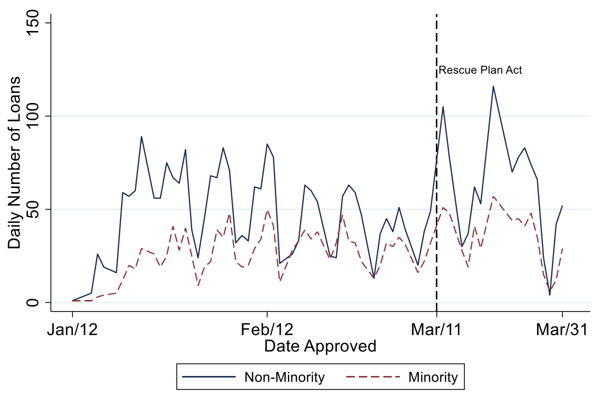
Appendix A Additional Figures



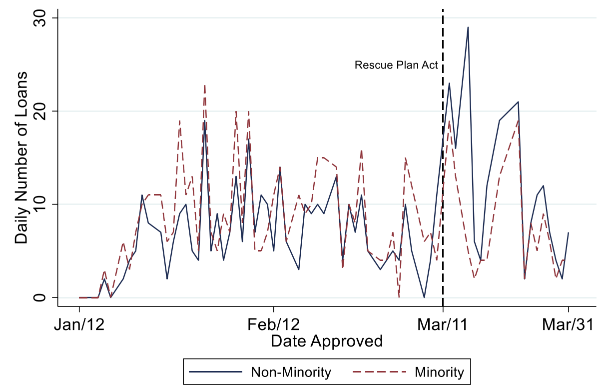
(a) 2020 PPP, Non-Fintech Lenders



(b) 2020 PPP, Fintech Lenders



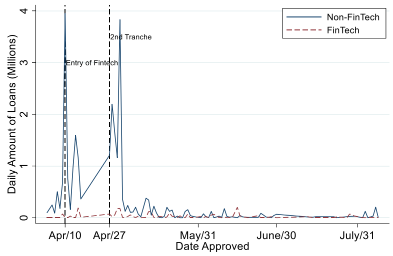
(c) 2021 PPP, Non-Fintech Lenders



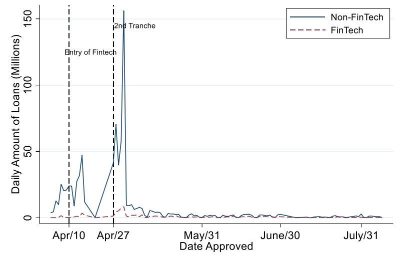
(d) 2021 PPP, Fintech Lenders

Figure A1 Minority- and Non-Minority-owned Businesses
Fintech vs. Non-Fintech (N. Loans)

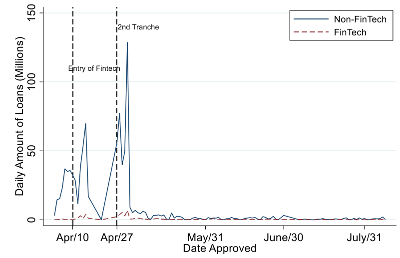
This figure plots the daily number of PPP loans received by minority- and non-minority-owned restaurants that are processed by non-fintech (Panel (a)) and fintech (Panel (b)) lenders in the 2020 PPP wave for our sample. The 2020 wave spans the period from April 3, 2020 and August 8, 2020. Similar plots for the 2021 program during January 12, 2021 and March 31, 2021 are in Panel (c) for non-fintech lenders and Panel (d) for fintech lenders. The y-axis represents the daily number of loans processed, and the x-axis represents the loan approval date. The blue solid line plots non-minority-owned restaurants and the red dashed line plots minority-owned restaurants. In Panels (a) and (b), the first vertical dashed line indicates the entry of fintech lenders on April 10, 2020 and the second vertical dashed line indicates the beginning of the second tranche of the 2020 PPP on April 27, 2020. In Panels (c) and (d), the vertical dashed line indicates the implementation of the American Rescue Plan Act of 2021 on March 11, 2021.



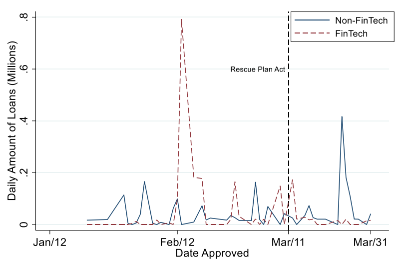
(a) 2020 PPP, African Americans



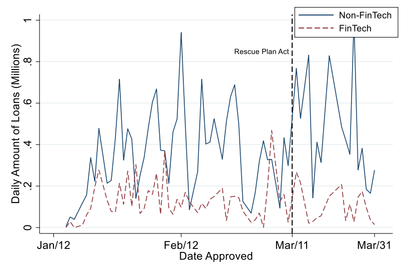
(b) 2020 PPP, Asians



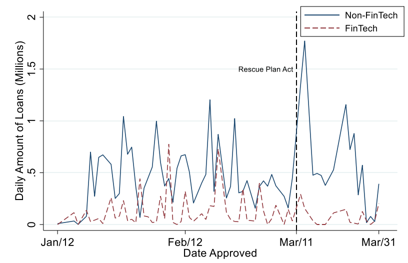
(c) 2020 PPP, Hispanics



(d) 2021 PPP, African Americans



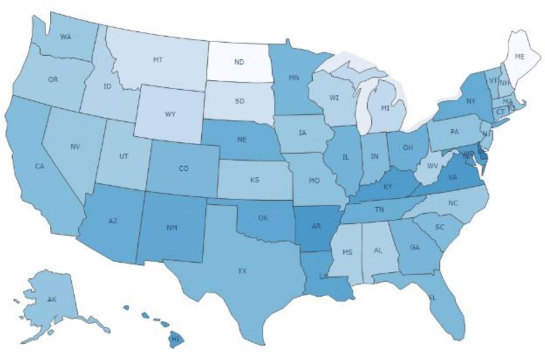
(e) 2021 PPP, Asians



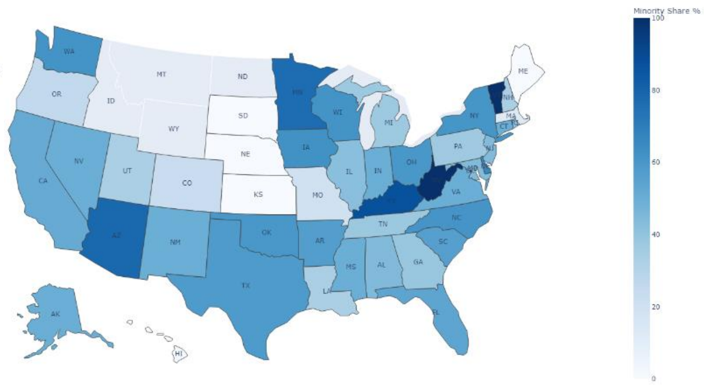
(f) 2021 PPP, Hispanics

Figure A2 Loans Distributed by Fintech and Non-Fintech Lenders Across Racial Groups (Dollar Value)

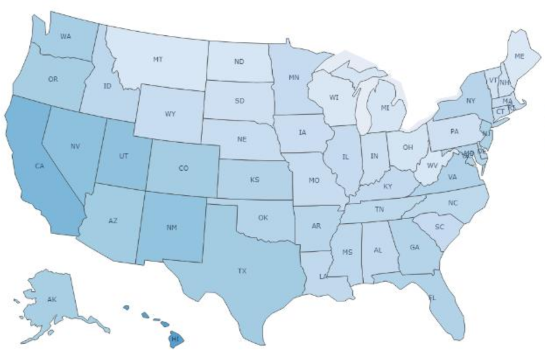
This figure plots the daily amount (USD millions) of PPP loans received by African American (Panel (a)), Asian (Panel (b)), and Hispanic (Panel (c)) borrowers in the 2020 PPP wave for our sample. The 2020 wave spans the period from April 3, 2020 and August 8, 2020. Similar plots for the 2021 program during January 12, 2021 and March 31, 2021 are in Panels (e) to (g) for African American, Asian, and Hispanic borrowers respectively. The y-axis represents the daily amount of loans processed, and the x-axis represents loan approval date. The blue solid line plots non-minority-owned restaurants and the red dashed line plots minority-owned restaurants. In Panels (a) to (c), the first vertical dashed line indicates the time of the entry of fintech lenders on April 10, 2020 and the second vertical dashed line indicates the time of the beginning of the second tranche of the 2020 PPP on April 27. In Panels (d) to (f), the vertical dashed line indicates the implementation of the American Rescue Plan Act of 2021 on March 11, 2021.



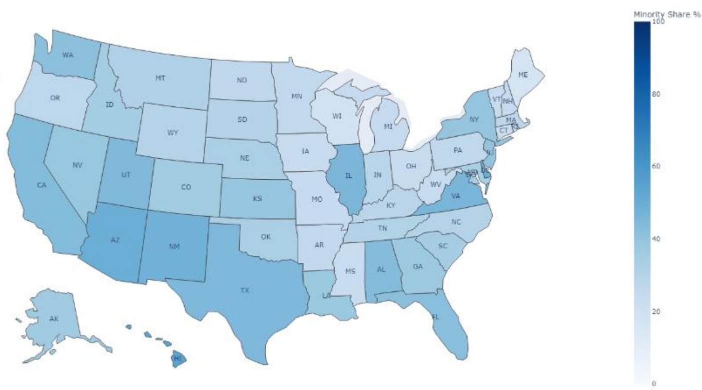
(a) Minority Share (Fintech) in 2020 PPP



(b) Minority Share (Fintech) in 2021 PPP



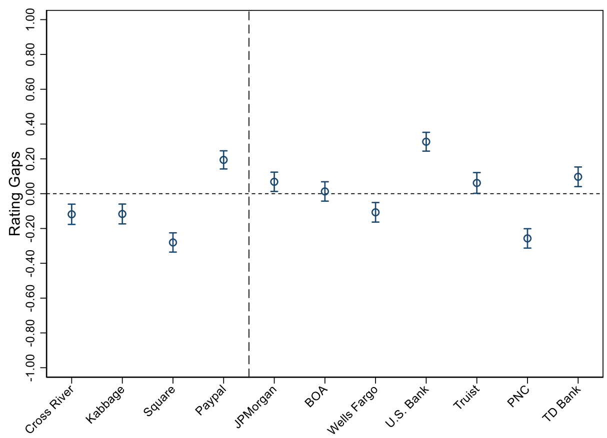
(c) Minority Share (Non-Fintech) in 2020 PPP



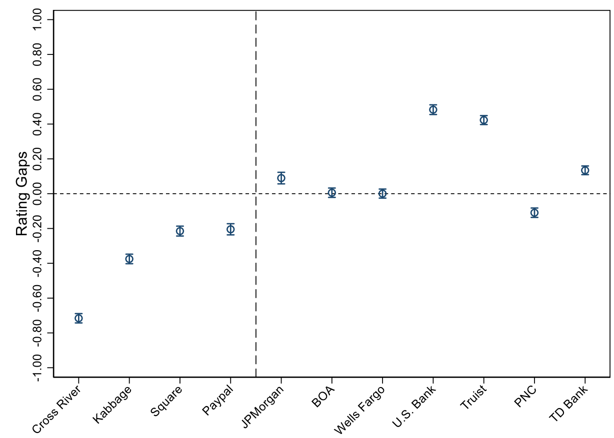
(d) Minority Share (Non-Fintech) in 2021 PPP

Figure A3 Percentage of Loans Distributed to Minority-owned Businesses
Fintech vs. Non-Fintech (N. of Loans)

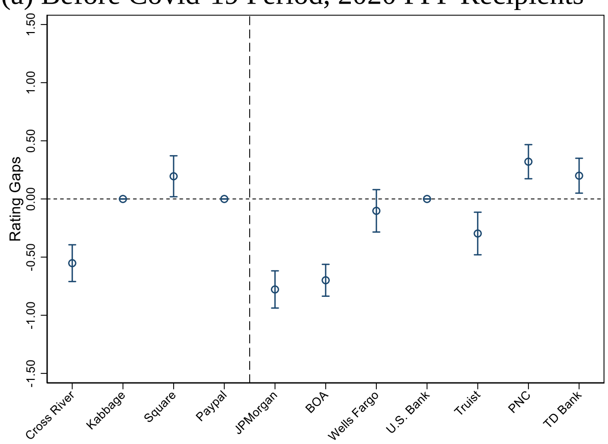
This figure plots the share of loan number distributed to minority-owned businesses processed by fintech (Panels (a) and (b)) and non-fintech (Panels (c) and (d)) lenders in the 2020 and 2021 waves, based on our sample. The *Minority Shares* range from 0% (the lightest blue) to 100% (the darkest blue).



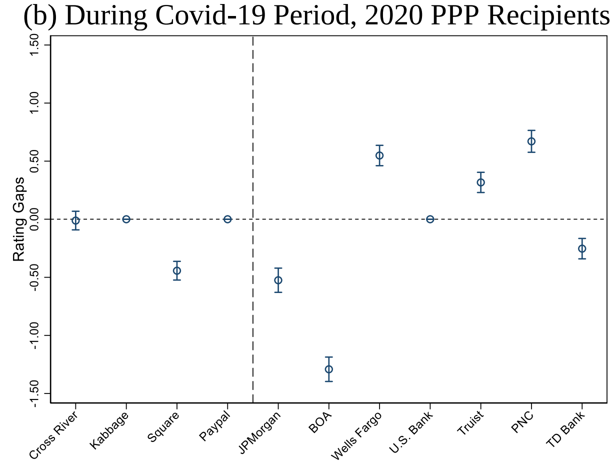
(a) Before Covid-19 Period, 2020 PPP Recipients



(b) During Covid-19 Period, 2020 PPP Recipients



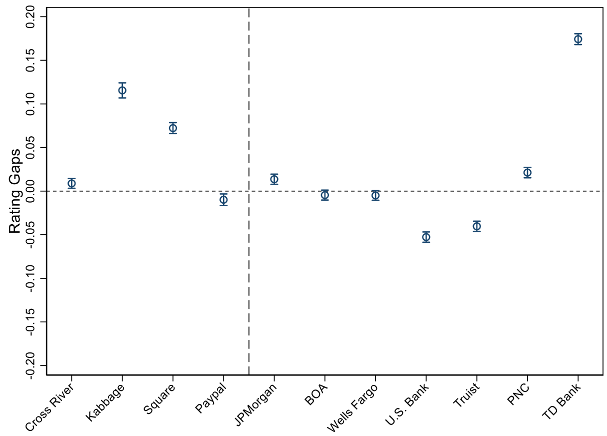
(c) Before Covid-19 Period, 2021 PPP Recipients



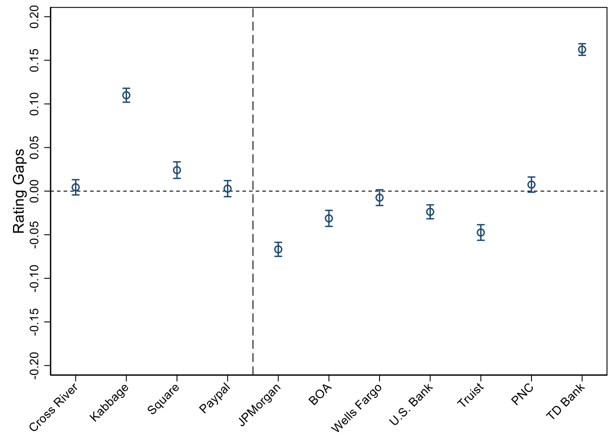
(d) During Covid-19 Period, 2021 PPP Recipients

Figure A4 Minority-Non-Minority Rating Gap (African-American-owned) Fintech vs. Non-Fintech

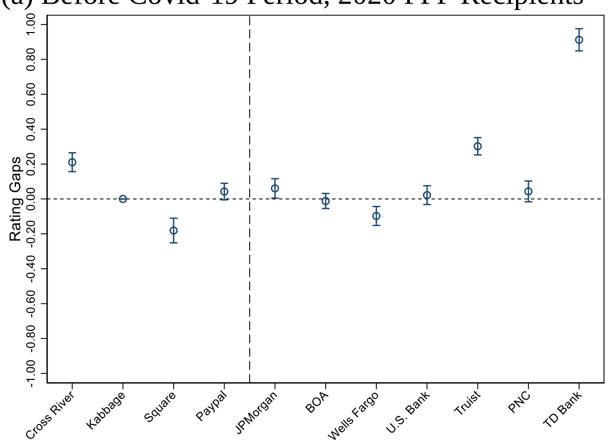
This figure plots the minority-non-minority rating gap for African-American-owned restaurants in the 2020 wave using historical ratings before the Covid-19 crisis (Panel (a)) and ratings during the Covid-19 crisis (Panel (b)), and for Asian-owned restaurants in the 2021 wave using the before-Covid ratings (Panel (c)) and during-Covid ratings (Panel (d)). The y-axis represents the coefficients before the interaction terms between the racial group indicator and lender indicators from the regressions as in Table 3, except that we decompose the fintech indicator into several dummies for each big fintech lender and bank. The x-axis represents each lender. We plot the biggest four fintech lenders in our sample: Cross River Bank, Kabbage, Square, and Paypal, and the largest seven banks in our sample: JPMorgan, Bank of America, Wells Fargo, U.S. Bank, Truist, PNC, and TD Bank. In each regression, the dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. The *African-American* indicator is defined to be 1 for restaurants that we identify as African-American food restaurants. The *Lender*$_j$ (*e,g.*, *Kabbage*) indicator is defined to be 1 for loans backed by that lender (e.g. by Kabbage). The omitted category is all other lenders. Control variables are the same as in Table 3 which contain lender dummies, racial group dummy, employment size, franchise dummy, month-city fixed effects, business type fixed effects, and eating policy dummies. Detailed variable definitions are in Appendix Table A1. Standard errors are clustered at the restaurant-lender level.



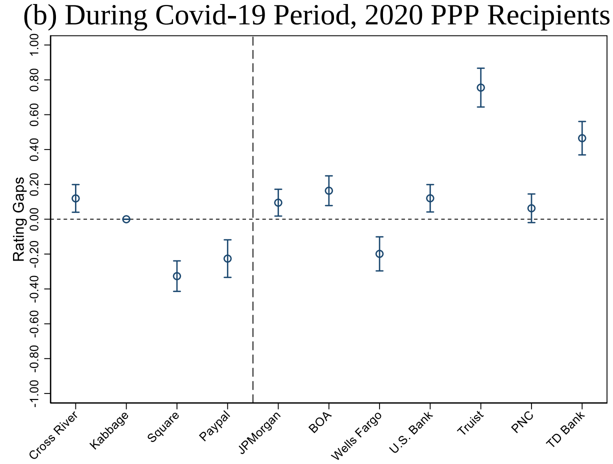
(a) Before Covid-19 Period, 2020 PPP Recipients



(b) During Covid-19 Period, 2020 PPP Recipients



(c) Before Covid-19 Period, 2021 PPP Recipients



(d) During Covid-19 Period, 2021 PPP Recipients

Figure A5 Minority-Non-Minority Rating Gap (Hispanic-owned)
Fintech vs. Non-Fintech

This figure plots the minority-non-minority rating gap for Hispanic-owned restaurants in the 2020 wave using historical ratings before the Covid-19 crisis (Panel (a)) and ratings during the Covid-19 crisis (Panel (b)), and for Asian-owned restaurants in the 2021 wave using the before-Covid ratings (Panel (c)) and during-Covid ratings (Panel (d)). The y-axis represents the coefficients before the interaction terms between the racial group indicator and lender indicators from the regressions as in Table 3, except that we decompose the fintech indicator into several dummies for each big fintech lender and bank. The x-axis represents each lender. We plot the biggest four fintech lenders in our sample: Cross River Bank, Kabbage, Square, and Paypal, and the largest seven banks in our sample: JPMorgan, Bank of America, Wells Fargo, U.S. Bank, Truist, PNC, and TD Bank. In each regression, the dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. The *Hispanic-owned* indicator is defined to be 1 for restaurants that we identify as Hispanic food restaurants. The *Lender*$_j$ (*e,g., Kabbage*) indicator is defined to be 1 for loans backed by that lender (e.g. by Kabbage). The omitted category is all other lenders. Control variables are the same as in Table 3 which contain lender dummies, racial group dummy, employment size, franchise dummy, month-city fixed effects, business type fixed effects, and eating policy dummies. Detailed variable definitions are in Appendix Table A1. Standard errors are clustered at the restaurant-lender level.

Appendix B Additional Tables

Table B1 Compare Our Sample with the Sample in Erel and Liebersohn (2020)

The difference between our sample and the EL Sample can be attributed to 1) we exclude borrowers in the state of PR, and non-profit organizations; 2) We adjust the lender identity to either the originating or the servicing lender is the fintech lender. For example, because Celtic Bank Corporation is also the originator of loans by Square Capital in addition to Square Capital itself as the originator, we assign those loans where the originating and servicing lender pair is Celtic Bank Corporation and Square Capital as with Square Capital. Adding the number of loans by both Celtic Bank Corporation and Square Capital gives a close number to the EL sample. Taking these modifications into account, our sample is comparable with the EL sample.

	Our Sample		EL Sample	
	PPP 2020	PPP 2021	PPP 2020	Our/EL
Cross River Bank	185207	139381	198738	93%
Kabbage, Inc.	159823		196402	81%
Square Capital, LLC	75096	11013	0	
WebBank	74620	8377	76578	97%
Celtic Bank Corporation	65376		147317	44%
Readycap Lending, LLC	34232	33604	34261	100%
Loan Source Incorporated	33050	3594	0	
Intuit Financing Inc.	17792		19086	93%
Fundbox, Inc.	13454		14281	94%
FC Marketplace, LLC (dba Funding Circle)	5963	3775	6235	96%
BSD Capital, LLC dba Lendistry	3504	1310	4076	86%
Itria Ventures LLC	3028	194210	3556	85%
Sunrise Banks, National Association	1655	545	0	
Opportunity Fund Community Development	978	184	990	99%
FinWise Bank	693		699	99%

Table B2 Fintech Lenders and Minority Borrowers (Robustness – Minorities as One Group)

This table reports the linear probability regression results where the dependent variable is the *Fintech* loan indicator (0/1). The 2020 and 2021 PPP waves are indicated in column heads. *Minority* is an indicator defined to be 1 for restaurants with a minority racial group cooking style. The construction of the matched sample and control variables are the same as in Table 2. Detailed variable definitions are in Appendix Table A1. For demonstration purposes, the dependent variable is multiplied by 100. The sample is the linked restaurant-loan-level cross-sectional dataset. Standard errors are clustered at the city level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw

Dep. Var.	I(Fintech) × 100							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Minority)	4.78***	3.61***	4.55***	3.47***	8.24***	4.99***	7.96***	4.95***
	(0.28)	(0.29)	(0.28)	(0.29)	(1.06)	(1.46)	(1.08)	(1.48)
Employment	-0.07***	-0.07***	-0.15***	-0.15***	-0.15***	-0.13***	-0.28***	-0.30***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.03)	(0.05)	(0.05)	(0.07)
I(Franchise)	-0.43	-0.32	-0.10	-0.25	-3.03*	-7.78***	-2.47	-6.93**
	(0.32)	(0.33)	(0.36)	(0.38)	(1.78)	(2.73)	(1.88)	(2.84)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	92,556	88,873	86,095	82,426	6,266	4,150	6,022	3,984
Adjusted R^2	0.037	0.058	0.039	0.060	0.059	0.078	0.059	0.085

Table B3 Minority-Non-Minority Rating Gap (Robustness –Minorities as One Group)

This table reports the regression results of the robustness check of Table 3 by combining *African American*, *Asian*, and *Hispanic* indicators into one minority indicator. As effects vary across different minority groups, we report the results of the specifications using decomposed group indicators in the main text. The regressions examine the difference in restaurant ratings between minority- and non-minority-owned restaurants that borrow from fintech and non-fintech lenders. The dependent variable is the *Rating Stars*, which range from 0 to 5, based on the customer reviews from yelp.com. In pane A and B, we report results on the 2020 PPP and 2021 PPP, respectively. *Minority* is an indicator defined to be 1 for restaurants with a minority racial group cooking style. The *Fintech* indicator is defined to be 1 for loans backed by fintech lenders. The construction of the matched sample and control variables are the same as in Table 3. Detailed variable definitions are in Appendix Table A1. The sample is the linked restaurant-loan monthly panel dataset where we calculate the monthly average of the ratings. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021. .Standard errors are clustered at the restaurant level and are reported in the parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw

Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Minority) × *I*(Fintech)	-0.06***	-0.06***	-0.06***	-0.06***	-0.04**	-0.02	-0.05**	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
I(Fintech)	0.05***	0.06***	0.05***	0.06***	0.05***	0.04**	0.04***	0.04**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
I(Minority)	-0.08***	-0.07***	-0.09***	-0.08***	-0.06***	-0.06***	-0.06***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	1032002	974781	959322	902934	464639	434948	432598	403363
Adjusted R^2	0.046	0.067	0.043	0.064	0.051	0.072	0.048	0.069

Panel B: 2021 PPP First Draw

Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Minority) × *I*(Fintech)	0.04	0.08	0.04	0.09	-0.08	-0.10	-0.07	-0.08
	(0.05)	(0.08)	(0.05)	(0.08)	(0.06)	(0.09)	(0.06)	(0.09)
I(Fintech)	-0.06*	-0.07	-0.07*	-0.08	-0.06	-0.02	-0.07	-0.03
	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)
I(Minority)	-0.12***	-0.10***	-0.13***	-0.10***	-0.09***	-0.04	-0.09***	-0.04
	(0.02)	(0.04)	(0.02)	(0.04)	(0.02)	(0.04)	(0.03)	(0.04)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	51844	29256	50102	28211	26491	14723	25476	14095
Adjusted R^2	0.039	0.048	0.039	0.049	0.039	0.048	0.038	0.045

Table B4 Minority-Non-Minority Rating Gap (Extensions –Non-Fintech or Fintech)

This table reports the regression results of the extensions of Table 3 by separating the sample into fintech and non-fintech borrowers. The regressions examine the difference in restaurant ratings between minority and non-minority borrowers. The dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. In pane A and B, we report results on the 2020 PPP wave for the non-fintech and fintech borrowers, and in Panel C and D on the 2021 PPP wave, respectively. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The *Fintech* indicator is defined to be 1 for loans backed by fintech lenders. The construction of the matched sample and control variables are the same as in Table 3. Detailed variable definitions are in Appendix Table A1. The sample is the linked restaurant-loan monthly panel dataset where we calculate the monthly average of the ratings. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021. .Standard errors are clustered at the restaurant level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw, Non-Fintech-Backed Restaurants								
Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African)	0.12***	0.15***	0.11***	0.14***	0.05	0.06	0.04	0.04
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
I(Asian)	-0.09***	-0.07***	-0.09***	-0.08***	-0.03***	-0.03***	-0.04***	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
I(Hispanic)	-0.09***	-0.09***	-0.09***	-0.09***	-0.11***	-0.11***	-0.11***	-0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	937462	879943	867060	810503	421431	391707	390451	361284
Adjusted R^2	0.047	0.069	0.044	0.066	0.052	0.073	0.049	0.069
Panel B: 2020 PPP First Draw, Fintech-Backed Restaurants								
Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African)	-0.00	0.04	-0.01	0.04	-0.23**	-0.12	-0.24**	-0.13
	(0.07)	(0.07)	(0.07)	(0.07)	(0.10)	(0.11)	(0.10)	(0.11)
I(Asian)	-0.17***	-0.16***	-0.18***	-0.16***	-0.11***	-0.07**	-0.11***	-0.07***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)
I(Hispanic)	-0.09***	-0.08***	-0.10***	-0.08**	-0.13***	-0.11***	-0.14***	-0.12***
	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.04)	(0.03)	(0.04)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	94540	71809	92262	70006	43208	31725	42147	30882
Adjusted R^2	0.038	0.068	0.037	0.066	0.051	0.076	0.048	0.075

Table B4 Minority-Non-Minority Rating Gap (Extensions–Non-Fintech or Fintech) (Cont.)

Panel C: 2021 PPP First Draw, Non-Fintech-Backed Restaurants

Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African)	0.15	0.30**	0.14	0.28**	-0.05	0.00	-0.05	-0.00
	(0.11)	(0.13)	(0.11)	(0.13)	(0.11)	(0.12)	(0.11)	(0.12)
I(Asian)	-0.13***	-0.14***	-0.15***	-0.15***	-0.04	0.00	-0.05	0.00
	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.05)	(0.03)	(0.05)
I(Hispanic)	-0.13***	-0.10**	-0.12***	-0.10*	-0.16***	-0.10*	-0.15***	-0.09
	(0.03)	(0.05)	(0.03)	(0.05)	(0.04)	(0.06)	(0.04)	(0.06)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	42470	22148	40902	21290	21742	11207	20817	10676
Adjusted R^2	0.042	0.053	0.042	0.054	0.041	0.051	0.039	0.047

Panel D: 2021 PPP First Draw, Fintech-Backed Restaurants

Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African)	0.02	-0.01	0.02	-0.00	-0.22	-0.46*	-0.22	-0.49*
	(0.12)	(0.25)	(0.12)	(0.25)	(0.14)	(0.27)	(0.14)	(0.27)
I(Asian)	-0.09	-0.05	-0.08	-0.04	-0.03	-0.06	-0.03	-0.05
	(0.06)	(0.13)	(0.06)	(0.13)	(0.07)	(0.13)	(0.07)	(0.13)
I(Hispanic)	-0.04	0.04	-0.04	0.05	-0.33***	-0.43***	-0.33***	-0.42***
	(0.07)	(0.14)	(0.07)	(0.14)	(0.08)	(0.15)	(0.08)	(0.16)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	9373	3333	9199	3308	4749	1589	4659	1576
Adjusted R^2	0.029	0.045	0.028	0.042	0.040	0.029	0.041	0.022

Table B5 Previous Lending Relationships and Minority-owned Businesses (Full Sample)

This table reports the regression results from examining the difference in previous lending relationships between minority- and non-minority-owned restaurants for the full sample. In pane A and B, we report results on the 2020 PPP and 2021 PPP waves, respectively. The dependent variable in columns (1) and (2) is a dummy variable that equals 1 if the borrower had SBA 7(a) or 504 loans during 2009-2019. In columns (3) and (4), the dependent variable is the total number of SBA 7(a) or 504 loans during 2009-2019. In columns (5) and (6), the dependent variable is the value (in USD millions) of SBA 7(a) or 504 loans during 2009-2019. *A. Loan* is winsorized at the 1% and 99% cuts. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The construction of the matched sample and control variables are the same as in Table 2.For demonstration purposes, all dependent variables are multiplied by 100, and *Employment* is divided by 100. The sample is the linked restaurant-loan-level cross-sectional dataset. Standard errors are clustered at the city level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	*I*(Rel.)	*I*(Rel.)	Rel. (N. Loans)	Rel. (N. Loans)	Rel. (A. Loan)	Rel. (A. Loan)
I(African)	-0.92	-1.02	-1.12	-1.31	-0.20	-0.35
	(0.66)	(0.68)	(1.07)	(1.12)	(0.33)	(0.33)
I(Asian)	-0.78***	-1.04***	-1.18***	-1.48***	-0.11	-0.29***
	(0.16)	(0.18)	(0.22)	(0.25)	(0.08)	(0.10)
I(Hispanic)	-1.05***	-0.98***	-1.54***	-1.37***	-0.25***	-0.32***
	(0.15)	(0.17)	(0.20)	(0.22)	(0.09)	(0.09)
Employment	0.63***	0.52**	1.46***	1.28***	1.35***	1.32***
	(0.20)	(0.21)	(0.38)	(0.40)	(0.18)	(0.18)
I(Franchise)	3.84***	3.80***	4.21***	4.13***	2.19***	2.12***
	(0.28)	(0.30)	(0.37)	(0.40)	(0.17)	(0.18)
City FEs		X		X		X
Business Type FEs	X	X	X	X	X	X
Observations	92556	88873	92556	88873	92556	88873
Adjusted R^2	0.011	0.008	0.008	0.004	0.010	-0.013
Panel B: 2021 PPP First Draw						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	*I*(Rel.)	*I*(Rel.)	Rel. (N. Loans)	Rel. (N. Loans)	Rel. (A. Loan)	Rel. (A. Loan)
I(African)	0.72	1.89	0.38	1.53	-0.24	-0.14
	(1.69)	(2.31)	(1.70)	(2.37)	(0.20)	(0.27)
I(Asian)	-0.45	-0.05	-0.71	-0.03	-0.23**	-0.35*
	(0.40)	(0.56)	(0.46)	(0.64)	(0.10)	(0.21)
I(Hispanic)	-0.65	0.05	-0.89*	0.12	-0.20	-0.08
	(0.44)	(0.66)	(0.52)	(0.76)	(0.16)	(0.22)
Employment	2.51	2.03	2.65	2.46	1.51**	1.69*
	(2.05)	(1.61)	(2.17)	(2.11)	(0.72)	(0.99)
I(Franchise)	1.45	1.47	1.68	2.10	0.39	0.58
	(0.93)	(1.19)	(1.17)	(1.60)	(0.32)	(0.47)
City FEs		X		X		X
Business Type FEs	X	X	X	X	X	X
Observations	6266	4150	6266	4150	6266	4150
Adjusted R^2	0.005	0.013	0.005	0.041	0.003	-0.094

Table B6 Fintech Lenders and Previous Lending Relationships (Full Sample)

This table reports the linear probability regression results where the dependent variable is the *Fintech* loan indicator (0/1). The key independent variables are *I(Rel.)*, a dummy variable that equals 1 if the borrower has borrowed SBA 7(a) or 504 loans during 2009-2019, *Rel. (N. Loans)*, the total number of SBA 7(a) or 504 loans borrowed during 2009-2019, and *Rel. (A. Loans)*, the million amount of SBA 7(a) or 504 loans borrowed during 2009-2019. In pane A and B, we report results on the 2020 and 2021 PPP waves, respectively. *A. Loan* is winsorized at the 1% and 99% cuts. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The control variables are the same as in Table 2. Detailed variable definitions are in Appendix Table A1. For demonstration purposes, the dependent variable is multiplied by 100. The sample is the linked restaurant-loan-level cross-sectional dataset. Standard errors are clustered at the city level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw						
Dep. Var.	*I*(Fintech) × 100					
	(1)	(2)	(3)	(4)	(5)	(6)
I(Rel.)	-5.74***	-5.22***				
	(0.44)	(0.48)				
Rel. (N. Loans)			-3.53***	-3.18***		
			(0.36)	(0.38)		
Rel. (A. Loan)					-4.69***	-4.85***
					(0.70)	(0.72)
Employment	-0.07***	-0.07***	-0.07***	-0.07***	-0.07***	-0.07***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
I(Franchise)	-1.49***	-1.16***	-1.56***	-1.23***	-1.62***	-1.27***
	(0.32)	(0.32)	(0.32)	(0.32)	(0.32)	(0.32)
City FEs	No	Yes	No	Yes	No	Yes
Business Type FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	92556	88873	92556	88873	92556	88873
Adjusted R^2	0.032	0.056	0.032	0.056	0.031	0.056
Panel B: 2021 PPP First Draw						
Dep. Var.	*I*(Fintech) × 100					
	(1)	(2)	(3)	(4)	(5)	(6)
I(Rel.)	-15.29***	-11.21***				
	(0.87)	(1.95)				
Rel. (N. Loans)			-11.51***	-8.52***		
			(0.98)	(1.56)		
Rel. (A. Loan)					-17.25***	-14.07***
					(4.58)	(3.23)
Employment	-0.17***	-0.14***	-0.17***	-0.14***	-0.17***	-0.14***
	(0.03)	(0.05)	(0.03)	(0.05)	(0.03)	(0.05)
I(Franchise)	-4.73***	-9.10***	-4.76***	-9.09***	-4.89***	-9.17***
	(1.80)	(2.71)	(1.80)	(2.71)	(1.79)	(2.70)
City FEs	No	Yes	No	Yes	No	Yes
Business Type FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6266	4150	6266	4150	6266	4150
Adjusted R^2	0.051	0.076	0.051	0.076	0.049	0.075

Table B7 Business Capital (Full Sample)

This table reports the regression results from examining the impact of business capital on the difference in the minority-non-minority rating gap between fintech and non-fintech lenders. The dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. Business Capital (*BC*) is proxied by the total number of ratings in the entire period of our analysis (from April 2018 to March 2021). *BC* is divided by 100 for demonstration purposes and winsorized at the 99% cuts. Sample periods are indicated in the column heads. Control variables are the same as in Table 3. Detailed variable definitions are in Appendix Table A1. *Employment* is divided by 100 for demonstration purposes. The sample is the linked restaurant-loan monthly panel dataset where we calculate the monthly average of the ratings. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021. Standard errors are clustered at the restaurant level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	**Rating Stars**							
Sample	2020 PPP First Draw				2021 PPP First Draw			
	Before Covid-19		During Covid-19		Before Covid-19		During Covid-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.) × *I*(FT) × BC	0.06	0.07	0.03	0.02	-0.01	-0.08	-0.01	0.00
	(0.04)	(0.04)	(0.13)	(0.11)	(0.09)	(0.12)	(0.08)	(0.12)
I(Asia.) × *I*(FT) × BC	0.10***	0.09***	0.07***	0.07***	0.23***	0.28***	0.11**	0.15***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.05)	(0.04)	(0.05)
I(Hisp.) × *I*(FT) × BC	0.12***	0.11***	0.09***	0.08***	0.05	-0.01	-0.09	-0.19*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.06)	(0.09)	(0.08)	(0.11)
I(FT)	-0.02**	-0.01	-0.01	-0.01	-0.10***	-0.09**	-0.11***	-0.09*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.03)	(0.05)
I(African)	0.11***	0.13***	0.01	0.03	0.12	0.25**	-0.08	-0.08
	(0.03)	(0.03)	(0.04)	(0.04)	(0.10)	(0.12)	(0.10)	(0.12)
I(Asian)	-0.10***	-0.09***	-0.04***	-0.04***	-0.16***	-0.15***	-0.05**	-0.03
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.04)	(0.03)	(0.04)
I(Hispanic)	-0.10***	-0.09***	-0.12***	-0.12***	-0.12***	-0.07	-0.19***	-0.13**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.03)	(0.05)
Employment	-0.12***	-0.12***	-0.11***	-0.12***	-0.35***	-0.33**	-0.38***	-0.43**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.11)	(0.15)	(0.10)	(0.19)
I(Franchise)	-0.89***	-0.87***	-1.06***	-1.02***	-0.91***	-0.84***	-0.92***	-0.82***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.06)	(0.08)	(0.07)	(0.10)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	1032002	974781	464639	434948	51844	29256	26491	14723
Adjusted R^2	0.047	0.067	0.052	0.072	0.041	0.052	0.041	0.050

Table B8 Relative Geographic Lending Scope (Full Sample)

This table reports the regression results from examining the impact of geographic lending scope on the difference in the minority-non-minority rating gap between fintech and non-fintech lenders for the full sample. The dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. Relative geographic lending scope (GS_r) is calculated as the total number of zip codes divided by the total number of cities that the lender covers in the entire PPP sample. CDFIs and CDCs are excluded because their lending scope may be restricted to certain communities. Sample periods are indicated in the column heads. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021. Control variables are the same as in Table 3. Detailed variable definitions are in Appendix Table A1. *Employment* is divided by 100 for demonstration purposes. The sample is the linked restaurant-loan monthly panel dataset where we calculate the monthly average of the ratings. Standard errors are clustered at the restaurant level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	**Rating Stars**							
Sample	2020 PPP First Draw				2021 PPP First Draw			
	Before Covid-19		During Covid-19		Before Covid-19		During Covid-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.)×*I*(FT)×GS_r	-0.08	-0.06	-0.16**	-0.15**	-0.08	-0.21	-0.08	-0.18
	(0.05)	(0.05)	(0.07)	(0.07)	(0.11)	(0.14)	(0.12)	(0.14)
I(Asian)×*I*(FT)×GS_r	-0.06***	-0.06***	-0.04***	-0.03*	0.01	0.05	-0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.06)	(0.04)	(0.06)
I(Hisp.)×*I*(FT)×GS_r	-0.01	0.01	-0.01	0.00	0.05	0.07	-0.12**	-0.19**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.07)	(0.06)	(0.09)
I(FT)	0.05***	0.06***	0.05***	0.04***	-0.06	-0.06	-0.05	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.06)	(0.04)	(0.06)
I(African)	0.12***	0.15***	0.04	0.06	0.15	0.31**	-0.07	-0.02
	(0.03)	(0.03)	(0.04)	(0.04)	(0.11)	(0.13)	(0.12)	(0.14)
I(Asian)	-0.08***	-0.07***	-0.03***	-0.03***	-0.13***	-0.13***	-0.03	-0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.03)	(0.04)
I(Hispanic)	-0.09***	-0.09***	-0.11***	-0.11***	-0.13***	-0.09*	-0.16***	-0.10*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.05)	(0.04)	(0.06)
Employment	-0.12***	-0.12***	-0.11***	-0.11***	-0.35***	-0.34**	-0.39***	-0.43**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.11)	(0.16)	(0.10)	(0.19)
I(Franchise)	-0.89***	-0.87***	-1.06***	-1.02***	-0.91***	-0.82***	-0.91***	-0.81***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.06)	(0.08)	(0.07)	(0.10)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	1025335	968144	461493	431821	51114	28634	26025	14342
Adjusted R^2	0.047	0.067	0.052	0.072	0.039	0.049	0.041	0.050

Table B9 Geographic Lending Scope – City vs Zip-Code Level (Matched Sample)

This table reports the regression results from examining the impacts of city- and zip-code-level geographic lending scope on the difference in the minority-non-minority rating gap between fintech and non-fintech lenders for the matched sample. The dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. Geographic lending scope at the zip code/city level (GS_{zip}/GS_{city}) is calculated as the total number of zip codes/cities that the lender covers in the entire PPP loan sample, divided by 10,000/1000 for demonstration purposes, and winsorized at the 99% cuts. CDFIs and CDCs are excluded because their lending scope may be restricted to certain communities. Credit unions are excluded for regression tractable reasons. Sample periods are indicated in the column heads. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021. The construction of the matched sample and control variables are the same as in Table 3. Detailed variable definitions are in Appendix Table A1. The sample is the linked restaurant-loan monthly panel dataset where we calculate the monthly average of the ratings. Standard errors are clustered at restaurant level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	Rating Stars							
Sample	2020 PPP First Draw				2021 PPP First Draw			
	Before Covid-19		During Covid-19		Before Covid-19		During Covid-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.)×I(FT)×GS_{city}	2.97***	2.73***	3.78***	2.14	1.00	5.45	-0.00	-0.07
	(0.65)	(0.71)	(1.39)	(1.55)	(1.58)	(5.46)	(0.10)	(0.13)
I(Afri.)×I(FT)×GS_{zip}	-17.60***	-16.22***	-22.80***	-13.20	-5.81	-32.34		
	(3.61)	(4.01)	(8.13)	(9.02)	(8.97)	(31.67)		
I(Asia.)×I(FT)×GS_{city}	0.75	1.43	2.24	3.04**	2.93	7.38	2.88	-0.23
	(1.04)	(0.99)	(1.41)	(1.30)	(4.46)	(6.60)	(2.92)	(3.35)
I(Asia.)×I(FT)×GS_{zip}	-4.66	-8.62	-13.22	-17.79**	-16.92	-42.65	-16.80	1.45
	(6.02)	(5.74)	(8.16)	(7.53)	(25.89)	(38.29)	(16.95)	(19.44)
I(Hisp.)×I(FT)×GS_{city}	1.08	1.28	1.17	0.71	0.97	16.78***	1.29	26.84***
	(1.05)	(1.14)	(1.28)	(1.27)	(8.23)	(1.78)	(0.97)	(2.18)
I(Hisp.)×I(FT)×GS_{zip}	-6.31	-7.39	-6.86	-4.14	-5.40	-97.13***	-8.13	-156.70***
	(6.12)	(6.64)	(7.42)	(7.36)	(47.77)	(10.28)	(5.57)	(12.62)
I(FT)	0.05***	0.06***	0.05***	0.04***	-0.07*	-0.07	-0.06	-0.04
	(0.01)	(0.01)	(0.01)	(0.01)	(0.04)	(0.06)	(0.04)	(0.07)
I(African)	0.11***	0.14***	0.04	0.04	0.04	0.23	-0.17	-0.12
	(0.03)	(0.03)	(0.04)	(0.05)	(0.12)	(0.14)	(0.13)	(0.16)
I(Asian)	-0.09***	-0.07***	-0.03***	-0.03***	-0.14***	-0.13***	-0.03	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.03)	(0.05)
I(Hispanic)	-0.09***	-0.09***	-0.11***	-0.11***	-0.12***	-0.08	-0.15***	-0.10*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.05)	(0.04)	(0.06)
Employment	-0.21***	-0.20***	-0.18***	-0.19***	-0.69***	-0.79***	-0.61***	-0.84***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.11)	(0.18)	(0.13)	(0.19)
I(Franchise)	-0.88***	-0.86***	-1.05***	-1.00***	-0.87***	-0.77***	-0.89***	-0.76***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.06)	(0.08)	(0.08)	(0.11)
Monthly FEs	Yes	No	Yes	No	Yes	No	Yes	No
City × Monthly FEs	No	Yes	No	Yes	No	Yes	No	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	923684	867831	416233	387260	47542	26314	24066	13059
Adjusted R^2	0.043	0.065	0.049	0.069	0.038	0.048	0.039	0.046

Table B10 Other Lenders: Lender-Type-Minority Rating Gap (Full Sample)

This table reports the regression results of restaurants that borrow from different types of lenders for the full sample. In Panel A, we compare banks that participate in SBA programs for the first time and banks who had previously participated in SBA programs. We use the SBA 7(a) and 504 loan-level data from 1990-2019 to identify lenders that participated in SBA programs before. We exclude fintech lenders and non-banks. In Panel B, we compare credit unions and other lenders in the FFIEC list. Panel C reports the regression results of CDFI or CDC versus banks. We exclude fintech lenders and other non-banks. The dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. The construction of the matched sample and control variables are the same as in Table 3. Detailed variable definitions are in Appendix Table A1. "Before Covid-19" refers to the period from April 2018 to March 2020, and "During Covid-19" refers to the period from April 2020 to March 2021. Standard errors are clustered at the restaurant level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: First-Time Bank

Dep. Var.	Rating Stars							
Sample	2020 PPP				2021 PPP			
	Before Covid-19		During Covid-19		Before Covid-19		During Covid-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri.) × *I*(New Bank)	-0.09	-0.07	0.09	0.07	0.71***	0.41	0.44*	0.30
	(0.13)	(0.16)	(0.15)	(0.19)	(0.15)	(0.25)	(0.24)	(0.31)
I(Asian) × *I*(New Bank)	-0.05	-0.02	-0.02	-0.02	0.29**	0.16	-0.06	0.14
	(0.04)	(0.04)	(0.04)	(0.05)	(0.15)	(0.30)	(0.16)	(0.35)
I(Hisp.) × *I*(New Bank)	0.02	0.02	0.03	0.02	-0.11	-0.25	-0.25	-0.32
	(0.04)	(0.04)	(0.04)	(0.05)	(0.13)	(0.22)	(0.18)	(0.32)
I(New Bank)	0.04**	0.03	-0.00	0.00	-0.04	0.15	0.19***	0.24*
	(0.01)	(0.02)	(0.02)	(0.02)	(0.08)	(0.18)	(0.07)	(0.13)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	915,513	858,150	411,222	381,574	39,695	20,147	20,145	10,090
Adjusted R^2	0.047	0.069	0.052	0.073	0.041	0.055	0.043	0.051

Panel B: Credit Union

Dep. Var.	Rating Stars							
Sample	2020 PPP				2021 PPP			
	Before Covid-19		During Covid-19		Before Covid-19		During Covid-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African Ame.)× *I*(CU)	-0.06	-0.08	-0.13	0.03	0.65***	0.47**	0.48**	0.61**
	(0.11)	(0.13)	(0.18)	(0.16)	(0.13)	(0.20)	(0.20)	(0.27)
I(Asian) × *I*(CU)	-0.03	-0.04	-0.13***	-0.12**	0.08	-0.14	-0.01	0.12
	(0.04)	(0.04)	(0.04)	(0.05)	(0.11)	(0.18)	(0.13)	(0.23)
I(Hispanic) × *I*(CU)	0.01	0.01	0.01	0.01	-0.18	-0.29	-0.01	0.26
	(0.04)	(0.04)	(0.04)	(0.05)	(0.15)	(0.18)	(0.14)	(0.27)
I(CU)	0.09***	0.09***	0.11***	0.11***	0.09	0.19**	0.11*	-0.11
	(0.01)	(0.02)	(0.02)	(0.02)	(0.06)	(0.09)	(0.07)	(0.14)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	952,321	895,771	427,705	398,417	43,203	22,546	21,815	11,194
Adjusted R^2	0.047	0.068	0.052	0.073	0.040	0.049	0.041	0.042

Table B10 Other Lenders: Lender-Type-Minority Rating Gap (Full Sample) (Cont.)

Panel C: CDFIs/CDCs

Dep. Var.	Rating Stars							
Sample	2020 PPP				2021 PPP			
	Before Covid-19		During Covid-19		Before Covid-19		During Covid-19	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afri. Ame.)× *I*(CDC)	-0.04	-0.04	0.05	-0.01	0.05	-0.22	0.23	0.22
	(0.11)	(0.12)	(0.15)	(0.17)	(0.20)	(0.32)	(0.29)	(0.36)
I(Asian) × *I*(CDC)	-0.24***	-0.21***	-0.07	-0.09	0.04	0.17	-0.30	-0.09
	(0.06)	(0.07)	(0.08)	(0.09)	(0.12)	(0.21)	(0.19)	(0.29)
I(Hispanic) × *I*(CDC)	-0.05	0.04	0.05	0.11	-0.02	-0.10	-0.06	0.32
	(0.07)	(0.07)	(0.09)	(0.10)	(0.15)	(0.28)	(0.19)	(0.28)
I(CDC)	0.20***	0.16***	0.07	0.04	0.13	0.15	0.17**	0.05
	(0.04)	(0.04)	(0.05)	(0.06)	(0.09)	(0.13)	(0.08)	(0.12)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	921,932	864,501	383,485	354,350	40,425	20,707	20,611	10,450
Adjusted R^2	0.047	0.069	0.048	0.069	0.041	0.056	0.042	0.053

Table B11 Non-Federally Insured Lenders

This table reports regression results on non-federally insured financial institutions. We restrict to the sample matched with the FFEIC lender list to have clear information on whether the lender is federally insured. In Panel A, we report the results on the linear probability regression of lender usage. The dependent variable is the *Uninsured* loan indicator (0/1) that equals 1 if the lender is not a federally insured financial institution. In Panels B and C, we report results on the rating gap in the 2020 and 2021 PPP waves, respectively. The dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. Matched sample construction and control variables are the same as in Table 2 (Panel A) and in Table 3 (Panel B and C). The sample is the linked restaurant-loan-level cross-sectional dataset (Panel A) and the linked restaurant-loan monthly panel dataset (Panels B and C). Standard errors are clustered at the city level (Panel A) and at the restaranut level (Panels B and C), and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Non-federally insured lender Usage

Dep. Var.	I(Uninsured) × 100							
Sample	2020 PPP				2021 PPP			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African)	1.00*	0.70	0.99*	0.70	-0.64***	-0.62	-0.62***	-0.66
	(0.58)	(0.56)	(0.59)	(0.57)	(0.22)	(0.54)	(0.23)	(0.56)
I(Asian)	0.27***	0.26**	0.22**	0.20*	2.21***	0.88	2.27***	0.90
	(0.10)	(0.11)	(0.10)	(0.11)	(0.57)	(0.70)	(0.58)	(0.72)
I(Hispanic)	-0.03	0.02	-0.05	0.01	-0.26	-0.64	-0.21	-0.57
	(0.08)	(0.08)	(0.08)	(0.08)	(0.32)	(0.46)	(0.32)	(0.47)
Employment	-0.00***	-0.00***	-0.01***	-0.00***	0.00	-0.01*	-0.00	-0.03**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.02)	(0.01)
I(Franchise)	-0.41***	-0.27***	-0.43***	-0.29***	-0.55*	-1.77***	-0.47	-1.79**
	(0.06)	(0.06)	(0.07)	(0.07)	(0.32)	(0.66)	(0.32)	(0.70)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	85349	81702	79145	75502	5298	3321	5079	3184
Adjusted R^2	0.001	0.053	0.001	0.052	0.008	0.038	0.009	0.039

Table B11 Non-Federally Insured Lenders (Cont.)

Panel B: Rating Gap (2020 PPP)

Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African) × *I*(Uninsured)	0.02	0.02	0.04	0.04	-0.16	-0.24	-0.14	-0.23
	(0.26)	(0.25)	(0.26)	(0.26)	(0.30)	(0.27)	(0.30)	(0.27)
I(Asian) × *I*(Uninsured)	-0.05	-0.09	-0.05	-0.10	-0.08	-0.08	-0.07	-0.08
	(0.07)	(0.08)	(0.08)	(0.09)	(0.09)	(0.10)	(0.09)	(0.10)
I(Hispanic) × *I*(Uninsured)	-0.17	-0.16	-0.17	-0.16	-0.09	-0.02	-0.09	-0.03
	(0.11)	(0.11)	(0.11)	(0.12)	(0.16)	(0.17)	(0.16)	(0.17)
I(Uninsured)	-0.04	0.03	-0.04	0.03	-0.05	-0.04	-0.06	-0.04
	(0.04)	(0.05)	(0.04)	(0.05)	(0.06)	(0.07)	(0.06)	(0.07)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	952321	895771	882486	826845	427705	398417	396912	368112
Adjusted R^2	0.047	0.068	0.043	0.065	0.052	0.073	0.048	0.069

Panel C: Rating Gap (2021 PPP)

Dep. Var.	Rating Stars							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African) × *I*(Uninsured)	-	-	-	-	-	-	-	-
I(Asian) × *I*(Uninsured)	-0.09	0.17	-0.08	0.13	-0.16	-0.18	-0.20	-0.18
	(0.22)	(0.41)	(0.21)	(0.41)	(0.20)	(0.37)	(0.20)	(0.38)
I(Hispanic) × *I*(Uninsured)	0.85***	0.75	0.82***	0.75	0.59***	0.12	0.52***	0.12
	(0.19)	(0.48)	(0.19)	(0.48)	(0.15)	(0.34)	(0.15)	(0.34)
I(Uninsured)	-0.13	-0.14	-0.12	-0.14	-0.05	0.20	0.00	0.20
	(0.18)	(0.41)	(0.18)	(0.40)	(0.14)	(0.32)	(0.13)	(0.32)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	43203	22546	41716	21715	21815	11194	20931	10694
Adjusted R^2	0.040	0.048	0.040	0.048	0.040	0.041	0.038	0.036

Table B12 Savings & Loan Association

This table reports regression results on savings & loan associations. We restrict to the sample matched with the FFEIC lender list to have a clear classification of S&L. In Panel A, we report the results on the linear probability regression of lender usage. The dependent variable is the *S&L* loan indicator (0/1) that equals 1 if the lender is a savings & loan association. In Panels B and C, we report results on the rating gap in the 2020 and 2021 PPP waves, respectively. The dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. Matched sample construction and control variables are the same as in Table 2 (Panel A) and in Table 3 (Panels B and C). The sample is the linked restaurant-loan-level cross-sectional dataset (Panel A) and the linked restaurant-loan monthly panel dataset (Panels B and C). Standard errors are clustered at the city level (Panel A) and at the restaranut level (Panels B and C), and are reported in the parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: S&L Usage Likelihood								
Dep. Var.	*I*(S&L) × 100							
Sample	2020				2021			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African)	-0.18***	-0.13*	-0.18***	-0.13*	-0.38***	-0.12	-0.33***	-0.12
	(0.03)	(0.08)	(0.03)	(0.07)	(0.12)	(0.08)	(0.11)	(0.08)
I(Asian)	-0.09***	-0.06**	-0.09***	-0.07**	-0.38***	-0.32*	-0.28***	-0.36*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.11)	(0.19)	(0.10)	(0.21)
I(Hispanic)	-0.01	0.00	-0.00	-0.00	-0.42***	-0.17	-0.28***	-0.19
	(0.04)	(0.04)	(0.04)	(0.04)	(0.12)	(0.13)	(0.10)	(0.13)
Employment	0.00	0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
I(Franchise)	-0.04	-0.05	-0.04	-0.06	-0.00	-0.07	-0.26***	-0.11*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.33)	(0.05)	(0.09)	(0.07)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	85349	81702	79145	75502	5298	3321	5079	3184
Adjusted R^2	-0.000	0.160	-0.000	0.157	0.001	0.109	-0.001	0.183

Panel B: Rating Gap								
Dep. Var.	**Rating Stars**							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African) × *I*(S&L)	-	-	-	-	-	-	-	-
I(Asian) × *I*(S&L)	0.06	0.14	0.09	0.14	0.26*	0.41**	0.28**	0.41**
	(0.19)	(0.18)	(0.19)	(0.18)	(0.14)	(0.17)	(0.14)	(0.18)
I(Hispanic) × *I*(S&L)	0.11	0.03	0.14	0.05	0.12	0.17	0.14	0.17
	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)	(0.18)
I(S&L)	0.02	0.05	-0.02	0.05	0.10	0.06	0.07	0.04
	(0.06)	(0.07)	(0.07)	(0.08)	(0.06)	(0.08)	(0.07)	(0.09)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	952321	895771	882486	826845	427705	398417	396912	368112
Adjusted R^2	0.047	0.068	0.043	0.065	0.052	0.073	0.048	0.069

Table B13 Capacity: Fintech vs Non-Fintech

This table reports the mean and standard deviation (in square brackets) of lender capacity, as measured by the number of loans disbursed in the PPP program in 2020 (upper panel) and in 2021 (lower panel) by fintech and non-fintech lenders, and the t-test results of the differences in capacity between fintech and non-fintech lenders. t-value are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2020 PPP First Draw			
	Fintech	Non-Fintech	Diff.
N. Loans	31052.79	617.85	-30434.9***
	[36602.76]	[6865.01]	(-27.75)
Observations	53	4199	
2021 PPP First Draw			
	Fintech	Non-Fintech	Diff.
N. Loans	12238.85	294.05	-11944.8***
	[34414.21]	[2803.07]	(-17.68)
Observations	46	4062	

Table B14 Approval Date (Robustness – Restricted Starting Date for the 2020 PPP)

This table reports the robustness check results of Table 11 in the 2020 PPP program by limiting the sample period to starting from April 9, 2020. This is because fintech lenders are not formally allowed in the program in the first week (April 03, 2020- April 08, 2020). In particular, as indicated in column heads, we do two sets of robustness checks by limiting the 2020 PPP sample to: 1) starting from April 09, 2020; 2) focusing on the second tranche in the 2020 PPP that started from April 27, 2020. The regressions examine the difference in PPP loan approval date between minority and non-minority borrowers who are matched with fintech and non-fintech lenders. The dependent variable is the *Δ(Approval Date-PPP Starting Date)*, where the starting date is April 03, 2020, and Jan 12, 2021, for the 2020 and 2021 programs correspondingly. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The *Fintech* indicator is defined to be 1 for loans backed by fintech lenders. The construction of the matched sample and control variables are the same as in Table 2. Detailed variable definitions are in Appendix Table A1. The sample is the linked restaurant-loan-level cross-sectional dataset. Standard errors are clustered at the city level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dep. Var.	Δ(Approval Date-PPP Starting Date)							
	From April 9, 2020				From April 27, 2020			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(African) × *I*(Fintech)	-2.00	-1.49	-2.00	-1.40	0.42	-0.68	0.39	-0.52
	(3.15)	(3.29)	(3.14)	(3.29)	(3.16)	(3.42)	(3.16)	(3.42)
I(Asian) × *I*(Fintech)	3.45***	3.68***	3.63***	3.88***	5.35***	4.22***	5.44***	4.38***
	(0.73)	(0.76)	(0.74)	(0.77)	(0.75)	(0.78)	(0.75)	(0.79)
I(Hispanic) × *I*(Fintech)	1.41	0.55	1.43	0.61	3.72***	2.87**	3.72***	2.94**
	(1.12)	(1.16)	(1.12)	(1.16)	(1.18)	(1.25)	(1.17)	(1.25)
I(Fintech)	12.10***	10.72***	11.61***	10.20***	7.75***	7.81***	7.46***	7.45***
	(0.46)	(0.50)	(0.47)	(0.51)	(0.47)	(0.51)	(0.47)	(0.51)
I(African)	7.63***	6.30***	7.12***	5.75***	3.61***	3.03**	3.44***	2.90**
	(1.26)	(1.31)	(1.27)	(1.33)	(1.31)	(1.36)	(1.33)	(1.38)
I(Asian)	8.60***	7.88***	8.12***	7.42***	4.24***	4.39***	4.13***	4.26***
	(0.30)	(0.32)	(0.30)	(0.32)	(0.29)	(0.31)	(0.29)	(0.31)
I(Hispanic)	4.56***	4.33***	4.44***	4.22***	1.69***	1.94***	1.74***	1.94***
	(0.28)	(0.30)	(0.29)	(0.30)	(0.33)	(0.35)	(0.33)	(0.35)
Employment	-0.08***	-0.08***	-0.18***	-0.18***	-0.07***	-0.06***	-0.14***	-0.12***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
I(Franchise)	-7.22***	-7.24***	-7.02***	-7.15***	-5.62***	-5.35***	-5.49***	-5.17***
	(0.23)	(0.25)	(0.25)	(0.27)	(0.31)	(0.35)	(0.32)	(0.37)
City FEs		X		X		X		X
Business Type FEs	X	X	X	X	X	X	X	X
Observations	81687	78026	76850	73244	56715	53348	54437	51109
Adjusted R^2	0.114	0.135	0.117	0.137	0.066	0.085	0.068	0.087

Table B15 Restaurant Ratings (Robustness –Approval Date Fixed Effects)

This table reports the robustness check results of Table 3 which examine the difference in ratings between minority- and non-minority-owned restaurants that borrow from fintech and non-fintech lenders. We add approval date fixed effects as control variables. Other than that, the specifications are the same as in Table 3. In Panels A and B, we report results on the 2020 and 2021 PPP waves, respectively. The dependent variable is the *Rating Stars*, which range from 0 to 5, based on customer ratings from yelp.com. *African American*, *Asian*, and *Hispanic* indicators are defined to be 1 for restaurants with the corresponding cooking style. The *Fintech* indicator is defined to be 1 for loans backed by fintech lenders. The construction of the matched sample and other control variables are the same as in Table 3. Detailed variable definitions are in Appendix Table A1. The sample is the linked restaurant-loan monthly panel dataset where we calculate the monthly average of the ratings. “Before Covid-19” refers to the period from April 2018 to March 2020, and “During Covid-19” refers to the period from April 2020 to March 2021. Standard errors are clustered at the restaurant level and are reported in the parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: 2020 PPP First Draw								
Dep. Var.	**Rating Stars**							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afr.) × *I*(Fintech)	-0.11	-0.09	-0.11	-0.08	-0.25**	-0.23**	-0.25**	-0.23**
	(0.08)	(0.08)	(0.08)	(0.08)	(0.11)	(0.11)	(0.11)	(0.11)
I(Asian) × *I*(Fintech)	-0.08***	-0.08***	-0.08***	-0.08***	-0.06***	-0.04	-0.06***	-0.04*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
I(Hispanic) × *I*(Fintech)	-0.01	0.01	-0.01	0.01	-0.01	0.01	-0.02	-0.00
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
I(Fintech)	0.06***	0.06***	0.06***	0.06***	0.05***	0.04**	0.05***	0.04**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	1032002	974781	959322	902934	464638	434947	432597	403362
Adjusted R^2	0.047	0.068	0.044	0.065	0.052	0.073	0.049	0.069
Panel B: 2021 PPP First Draw								
Dep. Var.	**Rating Stars**							
Sample	Before Covid-19				During Covid-19			
	Full Sample		Matched Sample		Full Sample		Matched Sample	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
I(Afr.) × *I*(Fintech)	-0.12	-0.32	-0.13	-0.35	-0.10	-0.25	-0.10	-0.27
	(0.17)	(0.21)	(0.16)	(0.21)	(0.18)	(0.21)	(0.18)	(0.22)
I(Asian) × *I*(Fintech)	0.01	0.08	0.01	0.09	-0.02	0.02	-0.01	0.05
	(0.06)	(0.09)	(0.06)	(0.09)	(0.07)	(0.10)	(0.07)	(0.10)
I(Hispanic) × *I*(Fintech)	0.07	0.11	0.07	0.10	-0.17**	-0.28**	-0.17**	-0.28**
	(0.07)	(0.11)	(0.07)	(0.11)	(0.09)	(0.13)	(0.09)	(0.13)
I(Fintech)	-0.07*	-0.07	-0.08*	-0.09	-0.07	-0.01	-0.07*	-0.02
	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.06)	(0.04)	(0.07)
Monthly FEs	X		X		X		X	
City × Monthly FEs		X		X		X		X
Other Controls	X	X	X	X	X	X	X	X
Observations	51844	29256	50102	28211	26491	14721	25476	14093
Adjusted R^2	0.042	0.054	0.042	0.056	0.043	0.057	0.042	0.054

Appendix C Data Construction

Appendix C1 Identify Fintech Lenders

The principal source of the fintech company list we used for our study is from the SBA official website as well as the local SBA websites. We start with the fintech company list published on sba.gov.[1] We manually read the PPP lender list published on the local SBA website of all states and find that the state of Arizona, California, Maryland, and North Carolina include a section on non-traditional lenders in their PPP lender lists. We include those lenders in the fintech company list as well. Finally, we also expand the list by consolidating lists from news sources below.

1. https://www.inc.com/brit-morse/fintechs-small-business-ppp-loan-applications.html
2. https://www.lendacademy.com/all-of-the-fintechs-involved-in-ppp-loans/
3. https://www.uschamber.com/co/run/finance/list-of-fintech-companies-offering-ppp-loans

We manually go through the entire sample of 165 non-bank lenders in the PPP loan-level dataset and do not identify any lenders that are clearly a fintech company but have not appeared in the above described sources. Some non-bank lenders may have collaborations with fintech companies but we do not include those cases because banks may also cooperate with fintech companies to some degree[2]. It is very time-consuming and might be impossible to identify all the partnerships between fintech companies and banks and other lenders, without adding more insights to our analysis.

Since the lists published on SBA websites and other news sources are primarily aimed to help borrowers to find a suitable platform or place to apply for the PPP loan, they may show the name of the lending platform instead of the lender backing the loan, and therefore not the same as the lender recorded in the PPP dataset. For each fintech company, we manually read their website and google search related information to identify the potential lender(s) associated with it. Table

[1]https://www.sba.gov/sites/default/files/resource_files/Fintech_Companies_Participating_in_PPP_05.08.20_0.pdf

[2] An example of unclear fintech lending of non-bank lenders in PPP: FundEx Solutions Group… representing the best of both traditional lending and fintech. An example of partnerships between fintech companies with other PPP lenders is "CNote has entered into a partnership with The Entrepreneur Fund to serve as a new capital source." Examples of banks work with fintech companies: Ally Bank, Bank of Hope, and Citizens Business Bank, etc. are shown to work with Lendistry in PPP.

C1-1 presents the consolidated fintech company list and the lender shown in the PPP dataset. In the table, we also indicate whether the fintech company is listed in the SBA or local SBA PPP lender list.

Table C1-1 Fintech company list and match with lender name in PPP data

Fintech company	SBA	AZ	MA	NC	CA	Lender Name in PPP
Biz2credit	Y			Y		Itria Ventures LLC; Loan Source Incorporated
BlueVine	Y	Y	Y	Y	Y	Cross River Bank
Brex + Womply*	Y					-
Credibly	Y	Y				-
Cross River Bank	Y			Y		Cross River Bank
Divvy	Y			Y		Cross River Bank
Forwardline Financial LLC		Y				FinWise Bank
Fundbox	Y	Y			Y	Fundbox, Inc.
Fundera*	Y			Y		-
Funding Circle	Y	Y	Y	Y	Y	FC Marketplace, LLC (dba Funding Circle)
Intuit (Quickbooks)	Y	Y	Y	Y	Y	Intuit Financing Inc.
Kabbage	Y	Y	Y	Y	Y	Kabbage, Inc.; Celtic Bank Corporation
Lendio	Y		Y	Y		Sunrise Banks, National Association
Lendistry			Y			BSD Capital, LLC dba Lendistry
NAV*	Y					-
OnDeck	Y	Y	Y		Y	Celtic Bank Corporation
Opportunity Fund Community Development		Y			Y	Opportunity Fund Community Development
Paypal	Y	Y	Y		Y	WebBank
Ready Capital	Y					Readycap Lending, LLC
Reliant Funding						Cross River Bank
SmartBiz*						-
Square	Y	Y	Y		Y	Celtic Bank Corporation
Veem	Y					Cross River Bank

* Partner with multiple lenders and do not find the fintech company itself in the PPP data

Appendix C2 Lenders Classifications and Matching with FFIEC

This appendix describes our lender classifications and how we match the PPP lenders with Federal Financial Institutions Examination Council (FFIEC) financial institutions. Based on the matched list of PPP and FFIEC lenders, we show how we define several key variables.

1. Lender Classification

To save some labor effort in the matching process with FFIEC, we first classify the PPP lender list into banks and non-banks. Within the non-banks, we classify lenders into CDFI/CDC, fintech non-banks, other non-banks.

1.1 Non-Banks

We start with the full list of 5,597 PPP lenders in the entire PPP and PPS dataset. The first step is to classify the lenders into banks (including savings, credit unions, farm credit system institutions, etc.). We use regular expressions on lender names, and define the lender as a bank if either the name of the originating and the servicing lender[3] satisfies the regular expression. Examples of regular expressions are containing "bank", ending with "N.A." or "National Association", and containing "Production Credit Association". For the part that does not contain expressions satisfying the regular expressions, and therefore in the list of non-banks, we manually checked them by searching on the official website and names and reassign 47 lenders into the bank list, such as AB&T, BBVA USA, and Choice Financial Group. This gives us 5,472 banks and 125 non-banks.

1.2 CDFI Loan Funds and 504 CDC

For the purpose of our study, we further classify the non-banks into lenders that have higher weights on community development and other non-bank lenders. We use two sources of information. First, we match the PPP lenders with the loan funds in the official list of "List of Certified Community Development Financial Institution (CDFIs) with Contact Information as of October 14, 2020" published on cdfifund.gov using exact name match. This gives 42 matches

[3] The difference between the servicing and originating lender is most relevant for fintech lenders and CDFIs, which we address in particular. For other lenders, the servicing and originating lender is the same.

considering either the servicing and originating lender is among the CDFI list. This step also adjusts one lender in the bank list, Hope Enterprise Corporation, into the non-bank list. In particular, one fintech lender in our list, Opportunity Fund Community Development, is also a CDFI. For the remaining 85 non-bank lenders, we manually check them with the official CDFI list and find 24 pairs of matched lenders. In the manual step, we also consider matching with either the servicing or the originating lender as valid matches.

Second, we identify Certified Development Company (CDC) using the list of lenders that participated in previous 504 programs. We adjust lender names using the lender cleaning code as in the process of other steps related to previous lenders. All identified CDCs are non-banks under our classification. We do not consider other non-banks whose names contain words like "community", and "development" but neither in the CDFI or the CDC list as community development-related lenders as the company name is not a precise indication.

In total, we identify 66 CDFIs and 23 CDCs, with 8 enter in both categories.

1.3 Fintech Non-Banks

Using our list of fintech lenders, we identify 14 fintech lenders in the non-bank part.

1.4 Other Non-Banks

After restricted to non-fintech lenders, we classify the rest 35 non-bank lenders in the category of other non-banks. As stated in the appendix describing our process to identify fintech lenders, we manually searched on google for more information for each lender and do not find any lender that is clearly stated as a fintech lender.

Code of the regular expressions, manually adjusted lender lists, and the final list of non-banks can be found on the corresponding author's website. Table C2-1 summarizes the number of pairs of originating and servicing lenders in each category.

Table C2-1 Number of Lender Pairs in Each Category

Category		N. in the entire PPP sample	N. in our final analysis sample
Banks	Fintech	49	42
	Non-fintech	5,420	4,134
Non-Banks	CDFI/CDC	81 (2 are also fintech lenders)	54 (2 are also fintech lenders)
	Fintech	14	11
	Others	35	27

2. Matching PPP Lenders with FFIEC

We then match the PPP lenders with financial institutions on the FFIEC list. Our starting sample is 3,695 PPP lenders who 1) are lenders in our final linked restaurant sample; 2) lend more than 100 loans in the entire PPP program; 3) banks (including fintech lenders) or other non-banks (excluding CDFI/CDC/fintech lenders) classified in step 1 described above.

Federal Financial Institutions Examination Council (FFIEC) lender information provides information on financial institutions for which the Federal Reserve has a supervisory, regulatory, or research interest, which includes a full list of depository institutions, as well as some non-depository financial companies. The data includes both active and the last instance of closed financial institutions and assigns a unique identifier (*ID RSSD*) for each financial institution. We keep financial institutions that are active in and after 2020 because PPP loans are originated after 2020. The data is available from the FFIEC website (ffiec.gov).

In the code-based matching step, we find a match among the FFIEC financial institutions for each PPP lender that has the same name in the same city. We use originator name, city, and state information from PPP. We use bank legal names from FFIEC. The city and state information that we use from FFIEC is the lender's headquarter physical location city. We search for different variants of the lender name in our matching process. For example, "XX FCU" in place of "XX Federal Credit Union". Given that we are searching within the city, the match is very unlikely to be a mismatch. This gives a total match of 3,511 lenders.

For the remaining 184 unmatched lenders, we manually search for the lender name from FFIEC website and match with the FFIEC lender with the same name (including same name but different variants), different city, but the FFIEC lender city is within 30miles distance from the PPP lender city in the same state. This gives a total match of 3,658 lenders. The remaining 37 unmatched lenders are classified as finance companies that are not included in the FFIEC lender sample.

The FFIEC website also provides Branch Data which are the last instance of branches whose head office is listed in the financial institution file. We include branches that are active in and after 2020. For PPP lenders with a matched *ID RSSD* identifier, we match the PPP lender with the branch's parent institutions, therefore, we can identify the branches that belong to each lender. For those PPP lenders with either no branch information from FFIEC branch data or no *ID RSSD* identifier, we classify them as stand-alone entities.

3. Further Classification for FFIEC Matched Lenders

For lenders matched with FEIEC, we classify lenders into banks vs non-banks, federally insured institutions vs non-federally insured institutions, credit union vs non-credit union, savings & loan association vs non- savings & loan association based on lender information from FFIEC.

Bank: We use a broad definition of banks as any depository institution. We identify depository institutions based on entity type from FFIEC lender information, including “Cooperative Bank”, “Domestic Branch of a Domestic Bank”, “Federal Credit Union”, “Federal Savings Bank”, “National Bank”, “Non-member Bank”, “Savings & Loan Association”, “State Credit Union”, “State Member Bank”, and “State Savings Bank”.

Federally Insured: A lender is classified as a federally insured institution if its primary insurer is either National Credit Union Share Insurance Fund or Deposit Insurance Fund.

Credit Union: Lenders whose entity types are “Federal Credit Union” or “State Credit Union” are classified as credit unions.

Savings & Loan Association: Lenders with entity types as “Savings & Loan Association” are defined as Savings & Loan Association.

4. Cross Validation and Final Lender Classification

Based on the consolidated lender dataset, only two lenders (New York Business Development Corporation, and American Lending Center) identified as non-banks by name in section 1 are matched with the FFIEC list and their entity type is “Domestic Entity Other (DEO)”. Among the banks identified by name and matched with the FFIEC list, only eight lenders are DEO; others are all in the bank group based on our classifications in step 3. Among the eight DEO lenders, five are farm credit institutions, and we adjust the rest three (First Western SBLC, Inc, Capital One, National Association, and First National Bank Texas) into the non-bank category. This gives additional validation of our code-based classification of banks and non-banks. Among the banks identified by name, only 17 are unmatched.

Appendix C3 Linking a Business Entity Participated in the Paycheck Protection Program with a Restaurant on Yelp.com

This appendix describes the steps that we follow to match businesses in the *Food Services and Drinking Places* sector (NAICS code that equals 722) in the Paycheck Protection Program (PPP) to the restaurants on yelp.com. It also presents the matching criteria based on which we define a link between a business in the PPP and a restaurant on yelp.com. In addition, we provide the details on the name and address cleaning process which we use as the input of automatic search and code-based match.

1. Matching Steps

Our start sample is the 372,541 loans assigned to businesses in the *Food Services and Drinking Places* sector in the two tranches of the first draw of the PPP program in both 2020 and 2021, which are labeled with "PPP" by the *Processing Method* variable in the original dataset from SBA. In addition, our sample also covers 198,889 loans in the *Food Services and Drinking Places* sector in the second draw of the PPP program in 2021, which are labeled with "PPS" by the *Processing Method* variable. After our name and address adjustments, we are also able to identify the first draw participants who reapplied for the second draw.

Step 1: Basic sample cleaning

The basic sample cleaning serves two purposes. First, by unifying and deleting suffix and prefix, the business name and address are more likely to be what appears on yelp.com, which facilitates our automatic search and code-based match process. Second, as we also study what types of borrowers participate in both the first and second draws of the PPP program, unifying and checking potential duplications makes the match across different years more reliable.

Step 1.1 Code-based adjustments of the business name

This step aims to adjust the names to be more likely to be what restaurants use as a trading name than a formal format of a company name. Details on the cleaning steps are described in *Section 3 Name and Address Cleaning Mapping*.

Step 1.2 Code-based adjustments of the business address

This step aims to adjust the addresses to be more likely to have a more unified format of different representations of the address code. Details on the cleaning steps are described in *Section 3 Name and Address Cleaning Mapping*.

Step 1.3 Manual check and adjustments potential duplicated business entities

The aim of this step is to assign a unique ID for each business entity that participated in the PPP and PPS. We assume that business entities in the same zip code region with the same name are the same restaurant and assign the same business entity ID to them. More specifically, two observations in the original data will be assigned with the same business entity ID if 1) the business name in the original dataset and the 5-digit zip code is the same for the two parts of the dataset; or 2) the adjusted name, adjusted address, and the 5-digit zip code are the same for the two parts of the dataset (the adjustment rules are described in *Section 3 Name and Address Cleaning Mapping*).

After excluding the repetition because of participation in both PPP and PPS, we have 3,500 observations that have the same adjusted business name and 5-digit zip code. We do two rounds of manual checks on these 3,500 observations. In the first round, we detect simple cases where the addresses are either exactly the same but written in different formats (e.g., "1502 j f kennedy dr" and "1502 jfk drive") or with a very small difference in the road number (e.g., "1651 w ogden ave" and "1659 w ogden ave"). We assign the same business entity ID to the two observations. After this round of checks, we have a rest of 1,370 observations. Then, we do a second round of manual checks and google searches to gain additional information to decide whether the business name and address in the dataset are for the same restaurant. We also gain the yelp link alongside. We find the yelp links for 1,058 observations, with 529 pairs for the same restaurant where we assign the same business entity ID and 44 observations that are different restaurants.

After the above described steps, we assign 371,845 unique business entity IDs to the 372,541 loans (less than 1% of the businesses are potentially applying for multiple loans.) Around 60% of participants in PPP also participated in the PPS.

Step 1.4 Basic adjustments of the franchise names

This step adjusts the franchise names in the PPP data to be close to the franchise names in real life. As the total number of franchise names (1,496) is relatively small, we do this step manually. We detect and delete some franchise names that are not for restaurant chains and the sample size decreases to 372,298 loans for the PPP sample and 198,642 loans for the PPS sample.

Step 2: Code-based automatic search of the adjusted business name and address on yelp.com.

We employ both the name search and address search on yelp.com to take into account the possibility that either one is better than the other when searching on yelp.com to find the most closely related restaurants. In both searches, we also include the zip code in the PPP data of the business entity to narrow the search range and increase the likelihood of a correct match. We use zip code instead of city because zip code is for a much smaller region than cities in most cases. In addition, as the city information in the original PPP data is with a lot of typos, using zip code instead of city can immune us from the noise in the original data.

We start with the name search as it can provide a better match when the restaurant's name is related to its company name. Name search also gives results on restaurants that are closed. After the name search, we match the search outcomes with the original PPP sample based on the matching criteria described in *Section 2 Matching Criteria*. If no match is found, we move on to the address search. While the name search may also give the correct results when the restaurant uses a different name than its company name, we complement the search results with address search to have a higher matching rate. For time-saving reasons, we include the first ten search results suggested by Yelp (i.e., the search outcomes on the first page on yelp.com) for our matching step. In most cases, Yelp search engine works with good precision and therefore it is very likely that the correct match is beyond the first ten results. Code for the search is available upon request.

One potential caveat in the search procedure is that the results suggested by Yelp might be incomplete and therefore we miss the correct match. However, as Yelp is a widely-used restaurant search engine with a good reputation, such a possibility is low and unlikely to be systematically biased.

Step 3: Match based on the combination of name and address

Our matching criteria are rather strict as we only include the pair as “matched” when we are confident that both the name and address in the two data sources have meaningful connections. We also put the restriction that the restaurant found on yelp.com is in the same 5-digit zip code region as in the PPP data.

Step 3.1 Code-based adjustments of the names and addresses

We employ the same code-based adjustments of the names and addresses as described in *Section 3 Name and Address Cleaning Mapping* for the counterparts in yelp to have a uniform representation of the same name/address. This step is important for improving the matching precision. For franchise names, we further shorten the names from the version used for automatic search as the names on yelp.com is shorter in most cases[4]. Code for this shortening step is available on the corresponding author’s website. We only do the shortening step for franchise names because, for non-franchised restaurants, two might only differ in the suffix.

Step 3.2 Code-based matching of the names and addresses based on different criteria

We use a code-based rule to narrow down and split the search outcomes into subsamples according to the connections between the PPP information and information on yelp.com for the adjusted and shortened version of the names and addresses. *Section 2 Matching Criteria* describes the detailed matching criteria.

Step 3.3 Manual check on a random sample for code-suggested matches under each criterion

To ensure the correctness of the matching process, we first manually check a random sample for the code-suggested matching sample for each criterion. For stricter matching criteria, the rate of correct matches is 100% or 98% and we consider all code-based matches under these criteria as “matched”.

Step 3.4 Manual correction of the matches for subsamples where the code-suggested matches are of low precision.

[4] Having parts that indicate food type such as “bbq”, “frozen”, and “cupcakery” in the version of names used for search is good for the search per se because yelp tend to suggest searching outcomes of the same food type.

When a random check suggests precision lower than 95%, we manually check and correct all the code suggested matches.

After the steps above, we have a sample of 104,429 total matches. We also add in the 556 matches from the manual step in 1.1, so we have a sample of 104,985 matches until this step.

Step 3.5 Other adjustments

There are very a few cases where one loan is matched with several yelp links. We manually check the 689 matches where the yelp link is duplicated. We pick the links that are more like to be a restaurant. For example, for some duplicates, one link is for a hotel and one link is for a restaurant in the hotel, then we pick the latter. When both links are for the same restaurant, we choose the one with more reviews or a more complete sample period before and after the Covid-19 crisis.

Until this step, we gain a matched sample for 104,296 loans, which accounts for 28.01% of the whole PPP sample in the *Food Services and Drinking Places* sector. Considering our rather strict matching criteria to ensure the likelihood of false positive to be very low, the matching rate is reasonable and the matched sample is useful. We further exclude the 1,769 observations where one yelp link is matched to multiple loans (1.70%, close to the percentage of potential multi-loan applications in the whole sample) and 724 observations where the yelp link is for a non-restaurant type business. We manually classify the business labels on yelp.com into labels for restaurants and non-restaurants. We publish the list of 546 yelp business labels related to our sample and our classification on the corresponding author's website.

Our final sample consists of 101,803 matches between a PPP loan and a yelp link for restaurants. We further exclude borrowers in Puerto Rico, Northern Mariana Islands, Guam, U.S. Virgin Islands when doing analysis.

2. Matching Criteria

This section describes the criteria based on which we identify as a match between a business entity in the PPP data and a restaurant on yelp.com, ranked from the most strict to the least strict ones. All criteria consider both the name and the address of the business.

Criterion 1: name the same/containing, address the same/containing, at least one is the same (75.65%)

Criterion 1 identifies matches where both the names and addresses in the PPP data and the yelp search outcomes are either exactly the same or with a relationship of one containing the other. We pose a restriction that at least one (name or address) is exactly the same. We check 100 random samples for each case of the different combination of name/address and exact/containing. In all cases, we have a 100% accuracy of matches for the random sample. Therefore, we consider all matches under criterion 1 are correct matches. Combining the matched search outcomes from both the name search and address search, we have 66,018 matches for non-franchise restaurants and 12,979 for franchise restaurants.

For the following criteria, we only consider the non-franchise sample because the following criteria are based on non-exact matching either for the name or the address which can only reasonably expand the matching sample for non-franchised restaurants. For names, since franchise names are already cleaned to a short version when used in the matching process and if there is no match found based on criteria 1, it is very unlikely to gain correct matches for more relaxed criteria. In addition, franchise restaurant names are already trading names so they are what appeared on yelp.com. For non-franchised restaurants, relaxing restrictions on names might be useful since some restaurants’ company name is quite different from the trading name. For addresses, non-franchised restaurants may put the corporation location or the business owner’s home address in the PPP data, and by relaxing matching to related restaurants in the same zip code region we can mitigate this data issue. Franchised restaurants cannot put the corporation location, which is the headquarter of the brand, in the PPP loan application. Franchised restaurant owners may also put their home address in the PPP application but we consider this type of mis-input to be of a much lower percentage for franchised restaurants than for non-franchised restaurants as the separation between the business and the owner is clearer in franchised restaurants than in a family-owned restaurant. Besides, given the high possibility of multiple restaurants under the same franchise brand in the same zip code region, we cannot easily identify correct matches if the address in the PPP data is not correct.

Criterion 2: name the same, zip code the same (9.92%)

Criteria 2 identifies matches where both the name and the 5-digit zip code in the PPP data and the yelp search outcomes are exactly the same. We check a 100 random sample and have a 98% accuracy of matches. Therefore, we consider all matches under criteria 2 are correct matches. Combining the matched search outcomes from both the name and address searches, we have 10,361 matches for non-franchise restaurants.

Criterion 3: name containing, address containing, zip code the same (6.01%)

Criterion 3 identifies matches where both the names and addresses in the PPP data and the yelp search outcomes are with a relationship of one containing the other. In addition, we pose the restriction that PPP data and the yelp search outcome are in the same 5-digit zip code. We check a 100 random sample and have a 100% accuracy of matches. Therefore, we consider all matches under criteria 3 are correct matches. Combining the matched search outcomes from both the name and address searches, we have 6,279 matches for non-franchise restaurants.

Criterion 4: name containing, zip code the same, with manual check and correction for all observations (8.42%)

Criterion 4 identifies where the names in the PPP data and the yelp search outcomes are with a relationship of one containing the other. In addition, we pose the restriction that PPP data and the yelp search outcome are in the same 5-digit zip code. We do not pose the condition that the addresses in both data sources have a containing relationship. We check a 100 random sample and the accuracy is low. Therefore, we manually check all code-suggested results and adjust the match when the one suggested by code matching is incorrect. After the manual correction, we have 8,792 matches for non-franchise restaurants, combining the matched search outcomes from both the name and address searches. Among them, 86.98% of the code matches are correct, with 6,225 are of addresses like typos or different formats, 1,283 are of addresses either or a home address or corporation office, 513 of a wrong yelp address. We correct the rest of the sample with a better match by google for additional information.

3. Name and Address Cleaning Mapping

3.1 Franchise Names

The 2021 March release of the data offers the franchise name of each small business if the company is a franchise chain company. For example, for subway, in the PPP loan-level data, the variable *FranchiseName* is “Subway”, and the variable *BorrowerName*, standing for the company name, can be “2 FRIENDSIN 2ND AVE INC.”, “AKOTA CORP.”, “FRESH SUBWAY 62 LLC”, etc. Since yelp.com shows the franchise brand name of the restaurants, we use the *FranchiseName* as the search input, instead of using the *BorrowerName* as in the search for non-franchised restaurants.

Early data entries of the PPP data might be incomplete and therefore we adjust the franchise name across the PPP and PPS whenever the franchise name is available for the same business entity ID.

We manually check the franchise names for the part of borrowers whose digit NAICS code starts with 722 (*Food Services and Drinking Places*). This step improves data quality in two dimensions. First, by unifying the franchise name into the brand name on yelp.com, the search and match procedure will be more accurate and thus can give us more correct PPP-Yelp matches. For example, the original franchise name can be “starbucks master licensing agreement” which contains parts (“master licensing agreement”) that are not related to the restaurant chain brand. Second, we detect franchise names that are clearly non-food services and drinking places. For instance, “Lamborghini America - dealer agreement” is a car brand, and “Laptopxchange” is an electronic service chain. We describe below the details on the criteria we use to judge whether the franchise name is a food or drinking place.

1) If the franchise name ends with the following keywords, we consider it as a food or drinking place: bagel, baguette, bakery, bar and grill/grill/grill and bar/grill and wings/ grill & cantina/ bar-b-que, bistro, bowl(s), burger(s), burrito, cafe/café, cakes, cantina, cha, chicken(s) (& biscuits), chocolate & gelato, coffee (shop), cookie dough/cookie(s), cuisine, custard, deli, dessert, donuts, eatery, frozen yogurt, gelato & caffe, hot dogs, iced creamery/ ice cream, juice (bar), kitchen, noodles/noodle, pretzel (or starting with), restaurant (including mis-spelling: resturant), salad, sandwich (shop), smoothies,

steakhouse/ steak house, street food, subs, sushi, tacos (or starting with taco)/taco shop, taphouse, taverna, tea(s), pasta, pizza/ pizzeria, wings, yogurt

2) If not, we search the franchise name in google with the restriction of only yelp.com webpages. If the search result returns a webpage in the restaurant/food category, we consider it as a food or drinking place. If all the search results on the first outcome page are not in the restaurant/food category, we google and check whether it is another type of franchise chain or not.
   Common miscategorized franchise names are art studios, car dealers, elderly care services, fitness clubs, optometrists, and training programs.
3) We do not exclude hotels in this step because some hotels also held an eating place. We exclude yelp pages of hotels in the manual matching step and the final other adjustment steps.

Among the 1,496 (1,332 for PPP only) franchise names associated with entries of a NACIS code that starts with 722, 201 (145) names are not associated with restaurants, accounting for 490 (243) loans. 52,080 (32,283) loans whose borrowers are of a NACIS code that starts with 722 are with a franchise name representing a restaurant chain. The false positive error rate is less than 1\% on the loan level. We drop the observations where the franchise name is not so we have 372,298 loans for the PPP sample and 198,642 loans for the PPS sample.

The full list of the adjusted and the original franchise names in the original PPP data of a NACIS code that starts with 722 is available on the corresponding author's website. In the list, we generate a name for the search step. We put "1" if the original name is clearly not for food services or drinking places, and the shortened brand name otherwise.

3.2 Non-franchised names

Non-franchised restaurants account for the majority of the sample, 340,015 loans (or 91.27%) after the adjustment of franchise names across the PPP and PPS sample. The large sample size makes it impossible to do manual adjustments and therefore we do code-based adjustments by deleting suffixes such as "corporation", "llc", "ltd". This serves the purpose to make the business name from the PPP data look more close to the potential restaurant trading name and facilitates the automatic search step. The cleaning code is on the corresponding author's website.

3.3 Address

The address cleaning step aims to cope with mainly two issues. First, it can unify the expressions across different data entries, for example, some entries may use “avenue” while some entries use “ave” for the same road type. Second, it also links more closely to the way addresses are expressed on yelp.com. The cleaning code is on the corresponding author’s website.

3.4 Examples Before and After Cleaning

Table C3-1 presents a sample of 10 random entries of the business name and address before and after adjustments.

Table C3-1

loannumber	businessname	businessname_org	address	address_org
4374000000	july 96	july 96 corp	2441 broadway	2441 broadway
4219000000	pb rams investment group	pb rams investment group	102 s main st	102 s main st
3521000000	ahta zahkung	ahta zahkung	318 hunt dr	318 hunt drive.
5662000000	k&a subs tyrone	k&a subs tyrone llc	3832 tyrone blvd	3832 tyrone blvd
8901000000	2 amegos	2 amegos inc	119 union st	119 union st
9764000000	la eda's restaurant	la eda's restaurant	1723 grand blvd	1723 grand blvd
1845000000	temple bill grill gp	temple bill grill gp	9768 bottoms rd	9768 bottoms road
7163000000	frankies other place	frankies other place inc	16036 red arrow hwy	16036 red arrow hwy
5586000000	summermoon coffee cedar valley	summermoon coffee cedar valley llc	1803 yaupon valley rd	1803 yaupon valley rd
1134000000	molly's corral	molly's corral llc	1519 w river rd	1519 west river road

4. Examples of the Linked Sample

Table C3-2 presents a sample of 10 random entries from our final linked sample on the PPP data and restaurant on yelp.com.

Table C3-2

https://www.yelp.com/biz/rockin-taco-and-tex-mex-frisco

loannumber	franchisename	businessname_org	address_org
2244000000		rockin taco & tex mex llc	6890 main st ste c

https://www.yelp.com/biz/dunkin-schenectady-3

loannumber	franchisename	businessname_org	address_org
2703000000	dunkin' donuts	schenectady donuts inc	1200 state st

https://www.yelp.com/biz/grimaldis-luna-park-east-syracuse-2

loannumber	franchisename	businessname_org	address_org
3715000000		grimaldi's luna park inc	6430 yorktown circle

https://www.yelp.com/biz/biergarten-los-angeles-4

loannumber	franchisename	businessname_org	address_org
4760000000		biergarten	206 n. western avenue

https://www.yelp.com/biz/pizza-market-west-newton

loannumber	franchisename	businessname_org	address_org
5312000000		hanna gakob inc (pizza market)	69 river street

https://www.yelp.com/biz/vitales-clam-bar-berlin

loannumber	franchisename	businessname_org	address_org
7926000000		vitale's clam bar llc	41 clementon rd

https://www.yelp.com/biz/hidden-fortress-coffee-roasting-watsonville

loannumber	franchisename	businessname_org	address_org
8055000000		hidden fortress coffee roasting llc	125 hangar way #270

https://www.yelp.com/biz/gaucho-parrilla-argentina-pittsburgh

loannumber	franchisename	businessname_org	address_org
8144000000		gaucho parrilla argentina	1601 penn ave

https://www.yelp.com/biz/club-37-baldwin

loannumber	franchisename	businessname_org	address_org
8196000000		club 37 inc	3803 n m 37

https://www.yelp.com/biz/five-spice-omaha-2

loannumber	franchisename	businessname_org	address_org
8863000000		five spice inc	2571 south 177th plaza

5. Sample Comparison: Linked versus Unlinked

Table C3-3 compares the summary statistics of key variables between PPP restaurant borrowers with a Yelp link and PPP restaurant borrowers without a Yelp link. The linked and unlinked sample looks similar to a reasonable degree.

Table C3-3

This table reports the mean of key variables between PPP restaurant borrowers with and without a Yelp link. The sample includes all restaurants borrowers in the PPP program in both years.

Panel A: PPP restaurant borrowers			
	UnLinked	Linked	Total
Initial Approval Amount	103368	77236	96221
Current Approval Amount	102801	77030	95753
Approved Date	06/27/2020	05/19/2020	06/16/2020
Jobs Reported	21	18	20
Franchise	0.074	0.121	0.087
Business Type:			
Corporation	0.292	0.339	0.304
Limited Liability Company	0.358	0.388	0.366
Partnership	0.024	0.030	0.025
Subchapter S Corporation	0.116	0.140	0.123
Sole Proprietorship	0.159	0.094	0.141
Self Employed	0.030	0.006	0.024
Others	0.021	0.003	0.016
Observations	270,432	101,799	372,231
Panel B: PPP restaurant borrowers(Excluded Sole Proprietorship, Self Employed, and Others)			
	UnLinked	Linked	Total
Initial Approval Amount	125372	82719	112592
Current Approval Amount	124691	82398	112020
Approved Date	5/21/2020	5/18/2020	5/20/2020
Jobs Reported	25	19	23
Franchise	0.092	0.132	0.104
Business Type:			
Corporation	0.369	0.377	0.372
Limited Liability Company	0.454	0.432	0.448
Partnership	0.030	0.034	0.031
Subchapter S Corporation	0.147	0.157	0.150
Observations	213,484	91,326	304,810

Table C4-4 shows the fintech share between PPP restaurants borrowers with a Yelp link and those without a Yelp link in each business type. For the business type of Corporation, Limited Liability Company, Partnership, Subchapter S Corporation, and Self Employed, the fintech share is similar for linked and unlinked samples. Restaurants with business type as Sole Proprietorship and Others have much a higher degree of fintech usage. Those are relatively smaller "restaurants" with limited types of services, for example, food trucks. Moreover, restaurants of a business type as Sole Proprietorship and Others are less likely to have a valid Yelp link, compared with other types of restaurants (see Table C4-4).

Table C3-4

This table reports the fintech share between PPP restaurant borrowers with and without a Yelp link for each business type. The sample includes all restaurant borrowers in the PPP.

	UnLinked		Linked		Total		
Business Type	FinTech	Obs.	FinTech	Obs.	FinTech	Obs.	Link Rate
Corporation	0.096	78865	0.101	34474	0.097	113339	0.304
Limited Liability Company	0.085	96931	0.085	39490	0.085	136421	0.289
Partnership	0.076	6374	0.089	3065	0.081	9439	0.325
S Corporation	0.087	31314	0.094	14297	0.089	45611	0.313
Sole Proprietorship	0.329	43130	0.089	9528	0.286	52658	0.181
Self Employed	0.588	8177	0.629	628	0.591	8805	0.071
Others	0.314	5641	0.095	317	0.302	5958	0.053
Total	0.133	270432	0.133	101799	0.133	372231	0.273

Table C4-5 compares the racial group shares based on the information in the PPP loan-level data for restaurant borrowers with and without a Yelp link. The sample includes all restaurant borrowers that have non-missing race and ethnicity information in the PPP dataset. Most of the race groups have a similar share for the linked and unlinked samples, except for African American borrowers. African American borrowers are less represented in the linked sample.

Table C4-5

This table reports the racial group shares based on the information in the PPP loan-level data for all restaurant borrowers that have non-missing race and ethnicity information. We report results for borrowers with and without a Yelp link and the entire sample.

	UnLinked	Linked	Total
White	0.488	0.570	0.509
Non-White	0.512	0.430	0.491
Hispanic	0.059	0.081	0.065
African American	0.217	0.043	0.173
Asian	0.204	0.267	0.220
Native American	0.031	0.039	0.033
Obs.	57,170	19,477	76,647

Appendix D Theoretical Matching Model Analysis

1. Additional Detailed Assumptions of the Matching Model

- We further assume that $M^m + M^n > M^f + M^b$. Therefore, not all borrowing demand is satisfied in equilibrium.
- We make the assumption that lenders do not directly screen borrowers to reflect the special case of the 100% government-guaranteed loans in the PPP program.
- Notice that we assume that the payoff function is increasing in the borrower’s rating γ_i. The exact distribution of the ratings of matched pairs in equilibrium depends on this assumption. However, our main result that the difference in the minority-non-minority rating gap between fintech lenders and banks implies that the payoff function is race biased does not depend on this assumption. The difference in the minority-non-minority rating gap is canceled out if the payoff function is race-neutral. This is also clear in our proof of Proposition 1.

2. Equilibrium of the Benchmark Case

We have a unique symmetric equilibrium that fintech lenders and banks are matched with minority and non-minority borrowers above the same threshold $\underline{\gamma}$, where $\underline{\gamma}$ is determined by

$$\delta M^m \int_{\underline{\gamma}}^{\infty} f(x, \mu^m, \sigma^m) dx + \delta M^n \int_{\underline{\gamma}}^{\infty} f(x, \mu^n, \sigma^n) dx = M^f \quad (D2.1)$$

$$(1-\delta) M^m \int_{\underline{\gamma}}^{\infty} f(x, \mu^m, \sigma^m) dx + (1-\delta) M^n \int_{\underline{\gamma}}^{\infty} f(x, \mu^n, \sigma^n) dx = M^b \quad (D2.2)$$

Where $f(\mu^m, \sigma^m)$ and $f(\mu^n, \sigma^n)$ are the density function of the normal distribution for the minority and non-minority borrowers respectively.

The logic of this equilibrium is the following. Suppose that the rating threshold to be matched with fintech lenders is lower (higher) than the rating threshold with banks, then borrowers between the two thresholds would deviate to fintech lenders (banks). There would be fintech lenders (banks) that are willing to accept those borrowers because their ratings are higher than their marginal borrowers. In equilibrium, the market cleans at the price (utility transferred) so that no deviation of borrowers can be profitable, which pushes the rating threshold to be the same for both types of lenders. In other words, because fintech lenders and banks have the same payoff function, neither type of lender has the incentive to have a lower matching threshold than the other.

As to the percentage of borrowers that are matched with fintech lenders and banks, it depends on the relative mass of lenders and borrowers. On the lender side, because lenders are indifferent between minority and non-minority borrowers, in the limit of a large sample, the same proportion of minority and non-minority borrowers are matched with a given type of lenders. On the borrower side, because borrowers are also indifferent between fintech lenders and banks, they choose randomly between different types of lenders. In the limit of a large sample, the percentage of borrowers matched with fintech lenders (δ) and with banks ($1-\delta$) depends on the relative mass of lenders and borrowers.

One important implication of the model is that a higher (lower) mean of the rating distribution results in a higher (lower) percentage of matched borrowers in equilibrium. This is because the part above the threshold is larger for a normal distribution with a larger mean. The effect of standard deviation depends on the exact parameter value as the density function of the normal distribution is $\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{(t-\mu)^2}{2\sigma^2}}$ where the standard deviation enters in two parts with opposite effects.

3. Race-Neutral Borrower-Lender Specific Payoff Case

In the second scenario, the payoff function depends on the rating of the borrower as well as a *race-neutral* borrower-lender specific factor $\theta_{i,j}$. We allow $\theta_{i,j}$ to interact with the rating γ_i to account for borrower self-selection effect or lender selection effect being related to rating.[5]

Tech Preference (Race-Neutral). In the race-neutral tech-preference case, we assume that higher-rated borrowers have a higher preference for technology and therefore have a higher payoff when matched with fintech lenders than with banks.[6] Notably, however, the tech-preference is race-neutral; minority and non-minority borrowers of the same rating level have the same additional preference for fintech lenders to banks. We normalize the tech-preference for banks to zero. For both minority and non-minority borrowers, $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i + \theta\gamma_i$ when matched with fintech lenders, and $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i$ when matched with banks.

[5] An additional utility θ without interaction with rating levels can be seen as a degenerated case.
[6] Similar to what explained in the detailed assumption 3, the direction of the relationship between ratings and tech-preference affects the explicit solution, but not the existence of the minority-non-minority rating gap.

The equilibrium in this setting is symmetric for minority and non-minority borrowers. The reasons are the following. Suppose that the matching threshold is higher for minority borrowers for lender *j*, then the minority borrower *k* at the margin of lender *j* would make an offer with a higher part of the transferred utility or deviate to other lenders. There would be other lenders happy to accept the minority borrower *k* because her rating is higher than the borrower at their margins and being minority does not lower the total payoff to be shared. In equilibrium, the market clears at the prices (transferred utilities) so that the matching threshold for minority and non-minority borrowers is the same for lenders of the same type.

However, the matching threshold is different for fintech lenders and banks because the preference for technology enters the payoff function directly. For a higher-rated borrower, she is willing to sacrifice a higher part of transferred utility when matched with fintech lenders, in return for the utility gain for technology. As a result, fintech lenders attract the part of borrowers with higher ratings and the rest of borrowers are matched with banks. The market clears at the prices so that the marginal borrower is indifferent between using fintech lenders and banks.

Formally, setting the outside option of borrowers to zero, the equilibrium is given by ($\underline{\gamma_f}$, $\underline{\gamma_b}$, p_f, p_b) that are determined by,

$$M^m \int_{\underline{\gamma_f}}^{\infty} f(x, \mu^m, \sigma^m)dx + M^n \int_{\underline{\gamma_f}}^{\infty} f(x, \mu^n, \sigma^n)dx = M^f \quad (D3.1)$$

$$M^m \int_{\underline{\gamma_b}}^{\underline{\gamma_f}} f(x, \mu^m, \sigma^m)dx + M^n \int_{\underline{\gamma_b}}^{\underline{\gamma_f}} f(x, \mu^n, \sigma^n)dx = M^b \quad (D3.2)$$

$$\underline{\gamma_f}(1+\theta) - p_f = \underline{\gamma_f} - p_b \quad (D3.3)$$

$$\underline{\gamma_b} - p_b = 0 \quad (D3.4)$$

Where $f(\mu^m, \sigma^m)$ and $f(\mu^n, \sigma^n)$ are the density function of the normal distribution for the minority and non-minority borrowers respectively.

Result Summary– Tech Preference (Race-Neutral). In the case where the payoff function depends on the borrower's rating as well as a race-neutral additional utility gain from fintech lenders, we have a race-neutral equilibrium in terms of rating levels. Due to the self-selection of higher-rated borrowers into fintech lenders, the average rating of borrowers matched with fintech lenders is higher for them than that for banks. The selection effect also implies that the ratio of shares of fintech-backed and non-fintech-backed borrowers is related to the underlying rating distribution, which is the main difference from the benchmark scenario. Given that the matching threshold is the same for minority and non-minority borrowers, and given that fintech lenders are matched with the part of borrowers above the matching threshold in our model, a larger mean of the rating distribution results in a larger matched area of fintech lenders.

Lending Relationship (Race-Neutral). The payoff function may differ for borrower-lender matches with and without previous lending relationships. We model the value of lending relationships in a simple way that the payoff function contains an additional utility component for borrower-lender matches with previous lending relationships. Since the major fintech lenders are new entrants in the SBA programs, we set lending relationships with fintech lenders to zero. In addition, the additional value of the lending relationship is the same for minority and non-minority borrowers; $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i + \theta\gamma_i$ when matched with banks with previous lending relationships, and $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i$ when matched with fintech lenders or banks without previous lending relationships.

To simplify notations, in the following presentation of the equilibrium, we assume that the fraction of borrowers who possess lending relationships is the same for minority and non-minority borrowers. This controls for that the ex-ante difference in lending relationships between minority and non-minority borrowers leads to a difference in the matched share between minority and non-minority borrowers in equilibrium. Relaxing this assumption changes the share of matches with fintech lenders and banks, but not the average rating level of matched pairs.

We have the following equilibrium,

$$(1-\delta)(1-\alpha)M^m \int_{\underline{\gamma_f}}^{\infty} f(x,\mu^m,\sigma^m)dx + (1-\delta)(1-\alpha)M^n \int_{\underline{\gamma_f}}^{\infty} f(x,\mu^n,\sigma^n)dx = M^f \quad (D3.5)$$

$$\alpha M^m \int_{\underline{\gamma_{b,r}}}^{\infty} f(x,\mu^m,\sigma^m)dx + \alpha M^n \int_{\underline{\gamma_{b,r}}}^{\infty} f(x,\mu^n,\sigma^n)dx$$
$$+\delta(1-\alpha)M^m \int_{\underline{\gamma_{b,nr}}}^{\infty} f(x,\mu^m,\sigma^m)dx + \delta(1-\alpha)M^n \int_{\underline{\gamma_{b,nr}}}^{\infty} f(x,\mu^n,\sigma^n)dx = M^b \quad (D3.6)$$

$$\underline{\gamma_f} - p_f = \underline{\gamma_{b,nr}} - p_f = \underline{\gamma_f} - p_b = \underline{\gamma_{b,nr}} - p_b \quad (D3.7)$$

$$\underline{\gamma_{b,nr}} - p_b = 0 \ (D3.8)$$

$$\underline{\gamma_{b,r}}(1+\theta) - p_b = 0 \ (D3.9)$$

Where $f(\mu^{m}, \sigma^{m})$ and $f(\mu^{nm}, \sigma^{nm})$ are the density function of the normal distribution for the minority and non-minority groups respectively. α is the fraction of borrowers with lending relationships with banks. $(D3.7)$ is the borrower's incentive compatibility constraint.

$$(D3.7) + (D3.8) + (D3.9) \Rightarrow \underline{\gamma_f} = \underline{\gamma_{b,nr}} \; and \; \underline{\gamma_{b,r}} = \frac{\underline{\gamma_{b,nr}}}{1+\theta}$$

Given that $\theta > 0$, the matching threshold is lower for borrowers possessing lending relationships than not possessing lending relationships. Borrowers not possessing lending relationships are indifferent between using fintech lenders and banks. In the limit of a large sample, δ is determined by the relative mass of fintech lenders and banks (M^{f} and M^{b}).

This gives that the equilibrium is characterized as $(\underline{\gamma}, \delta)$ by solving the following equations,

$$(1-\delta)(1-\alpha)M^{m}\int_{\underline{\gamma}}^{\infty} f(x, \mu^{m}, \sigma^{m})dx + (1-\delta)(1-\alpha)M^{n}\int_{\underline{\gamma}}^{\infty} f(x, \mu^{n}, \sigma^{n})dx = M^{f} \quad (D3.5')$$

$$\alpha M^{m}\int_{\frac{\underline{\gamma}}{1+\theta}}^{\infty} f(x, \mu^{m}, \sigma^{m})dx + \alpha M^{n}\int_{\frac{\underline{\gamma}}{1+\theta}}^{\infty} f(x, \mu^{n}, \sigma^{n})dx$$
$$+\delta(1-\alpha)M^{m}\int_{\underline{\gamma}}^{\infty} f(x, \mu^{m}, \sigma^{m})dx + \delta(1-\alpha)M^{n}\int_{\underline{\gamma}}^{\infty} f(x, \mu^{n}, \sigma^{n})dx = M^{b} \quad (D3.6')$$

Result Summary – Lending Relationship (Race-Neutral). In the case where the payoff function depends on the borrower's rating as well as a race-neutral additional utility gain from banks for the subset of borrowers with previous lending relationships, we have a race-neutral equilibrium in terms of rating levels. Because of the additional utility from lending relationships entering the total payoff function, the marginal borrower with lending relationships is of a lower rating level than the marginal borrower without lending relationships. This crowds out some higher-rated borrowers without lending relationships to fintech lenders. As a result, the average rating level is higher for fintech borrowers.

4. Race-Biased Borrower-Lender Specific Payoff Case

Tech Preference (Race-Biased). Now, we assume that the additional utility gain from technology is race-biased. We normalize the tech preference for banks to zero. We also normalize the racial bias in the tech preference for banks to zero. The payoff function is $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i + \theta^{m}\gamma_i$ ($p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i + \theta^{n}\gamma_i$) for minority (non-minority) borrowers when matched with fintech lenders, and $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i$ when matched with banks for both minority and non-minority borrowers.

Following the same logic as in the race-neutral case, an additional utility when matched with fintech lenders results in a higher matching rating threshold for fintech lenders than for banks. Unlike the race-neutral case, the equilibrium is race-asymmetric in the matching rating threshold for fintech lenders. ($\underline{\gamma_{mf}}$ and $\underline{\gamma_{nf}}$ are different.)

The key reasoning is the following. The incentive compatibility constraint of the marginal borrower implies that for fintech lenders, the market clears at the prices (transferred utilities) so that the racial group of borrowers associated with a higher level of tech preference (θ) are willing to offer a higher price to the lenders. Combined with the lender's incentive compatibility constraint which equates the transferred utility for the same type of lenders ($p_{mf} = p_{nf}$ and $p_{mb} = p_{nb}$), the matching threshold for fintech lenders is inversely related to tech preference. Proof of Proposition 1 presents the mathematical derivations.

Formally, setting the outside option of borrowers to zero, the equilibrium is given by ($\underline{\gamma_{mf}}$, $\underline{\gamma_{mb}}$, $\underline{\gamma_{nf}}$, $\underline{\gamma_{nb}}$, p_{mf}, p_{mb}, p_{nf}, p_{nb}) that are determined by

$$M^m \int_{\underline{\gamma_{mf}}}^{\infty} f(x, \mu^m, \sigma^m) dx + M^n \int_{\underline{\gamma_{nf}}}^{\infty} f(x, \mu^n, \sigma^n) dx = M^f \, (D4.1)$$

$$M^m \int_{\underline{\gamma_{mb}}}^{\underline{\gamma_{mf}}} f(x, \mu^m, \sigma^m) dx + M^n \int_{\underline{\gamma_{nb}}}^{\underline{\gamma_{nf}}} f(x, \mu^n, \sigma^n) dx = M^b \, (D4.2)$$

$$\underline{\gamma_{mf}}(1 + \theta^m) - p_{mf} = \underline{\gamma_{mf}} - p_{mb} \, (D4.3)$$

$$\underline{\gamma_{nf}}(1 + \theta^n) - p_{nf} = \underline{\gamma_{nf}} - p_{nb} \, (D4.4)$$

$$\underline{\gamma_{mb}} - p_{mb} = 0 \, (D4.5)$$

$$\underline{\gamma_{nb}} - p_{nb} = 0 \, (D4.6)$$

$$p_{mf} = p_{nf} \, (D4.7)$$

$$p_{mb} = p_{nb} \, (D4.8)$$

Result Summary – Tech Preference (Race-Biased). In the case where the payoff function depends on the borrower's rating as well as a race-biased additional utility gain from fintech lenders, the equilibrium is an asymmetry in matching rating thresholds. The racial group of borrowers having a higher value for fintech lenders are willing to offer a higher price to the lenders. However, the price the lenders can charge the marginal borrower is the same. As a result, the matching rating threshold for fintech lenders is smaller for that racial group of borrowers. In other words, the racial bias in the payoff function can be translated into a difference in the minority-non-minority rating gap between fintech lenders and banks in terms of the matching thresholds.

In the most real-world relevant case that minority borrowers have a stronger preference for fintech lenders, we observe not only a larger share of fintech users among minority borrowers even without differences in the underlying rating distribution across racial groups, but also a more negative minority-non-minority rating gap for fintech lenders than for banks. This does not exist in race-neutral payoff function cases.

Lending Relationship (Race-Biased). In this case, we study the situation where the additional utility component for previous lending relationships is different for minority and non-minority borrowers. We set the value of lending relationships with fintech lenders to zero. The payoff function becomes $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i + \theta^m \gamma_i$ ($p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i + \theta^n \gamma_i$) when matched with banks with previous lending relationships for minority (non-minority) borrowers, and $p_{i,j}(\gamma_i, \theta_{i,j}) = \gamma_i$ when matched with fintech lenders or banks without previous lending relationships for both types of borrowers.

The equilibrium is captured by,

$$(1-\delta)(1-\alpha)M^m \int_{\underline{\gamma_{mf}}}^{\infty} f(x, \mu^m, \sigma^m)dx + (1-\delta)(1-\alpha)M^n \int_{\underline{\gamma_{nf}}}^{\infty} f(x, \mu^n, \sigma^n)dx = M^f \quad (D4.9)$$

$$\alpha M^m \int_{\underline{\gamma_{mb,r}}}^{\infty} f(x, \mu^m, \sigma^m)dx + \alpha M^n \int_{\underline{\gamma_{nb,r}}}^{\infty} f(x, \mu^n, \sigma^n)dx$$

$$+\delta(1-\alpha)M^m \int_{\underline{\gamma_{mb,nr}}}^{\infty} f(x, \mu^m, \sigma^m)dx + \delta(1-\alpha)M^{nm} \int_{\underline{\gamma_{nb,nr}}}^{\infty} f(x, \mu^n, \sigma^n)dx = M^b \quad (D4.10)$$

$$\underline{\gamma_{mf}} - p_f = \underline{\gamma_{mb,nr}} - p_f = \underline{\gamma_{mf}} - p_b = \underline{\gamma_{mb,nr}} - p_b \quad (D4.11)$$

$$\underline{\gamma_{nf}} - p_f = \underline{\gamma_{nb,nr}} - p_f = \underline{\gamma_{nf}} - p_b = \underline{\gamma_{nb,nr}} - p_b \quad (D4.12)$$

$$\underline{\gamma_{mb,nr}} - p_b = 0 \quad (D4.12)$$

$$\underline{\gamma_{nb,nr}} - p_b = 0 \quad (D4.13)$$

$$\underline{\gamma_{mb,r}}(1+\theta^m) - p_b = 0 \quad (D4.14)$$

$$\underline{\gamma_{nb,r}}(1+\theta^n) - p_b = 0 \quad (D4.15)$$

Where $f(\mu^m, \sigma^m)$ and $f(\mu^n, \sigma^n)$ are the density function of the normal distribution for the minority and non-minority borrowers respectively. α is the fraction of borrowers possessing lending relationships.

$$\underline{\gamma_{mb,r}}(1+\theta^m) = \underline{\gamma_{nb,r}}(1+\theta^n) = \underline{\gamma_{mb,nr}} = \underline{\gamma_{nb,nr}} = \underline{\gamma_{mf}} = \underline{\gamma_{nf}} = \underline{\gamma} \; (D4.16)$$

Similarly, as in the race-neutral case, the matching threshold is lower for borrowers possessing lending relationships than for borrowers not possessing lending relationships. Moreover, the matching threshold is lower for the racial group of borrowers that the value of lending relationships is higher. Borrowers not possessing lending relationships are indifferent between using fintech lenders and banks. The equilibrium is characterized as $(\underline{\gamma}, \delta)$ by solving the following equations,

$$(1-\delta)(1-\alpha)M^m \int_{\underline{\gamma}}^{\infty} f(x, \mu^m, \sigma^m)dx + (1-\delta)(1-\alpha)M^n \int_{\underline{\gamma}}^{\infty} f(x, \mu^n, \sigma^n)dx = M^f \;\; (D4.9')$$

$$\alpha M^m \int_{\frac{\underline{\gamma}}{1+\theta^m}}^{\infty} f(x, \mu^m, \sigma^m)dx + \alpha M^n \int_{\frac{\underline{\gamma}}{1+\theta^n}}^{\infty} f(x, \mu^n, \sigma^n)dx$$
$$+\delta(1-\alpha)M^m \int_{\underline{\gamma}}^{\infty} f(x, \mu^m, \sigma^m)dx + \delta(1-\alpha)M^n \int_{\underline{\gamma}}^{\infty} f(x, \mu^n, \sigma^n)dx = M^b \; (D4.10')$$

We have the same property as in the race-biased tech preference case that the minority-non-minority rating gap in terms of the matching threshold is more negative for fintech lenders than for banks if $\theta^n > \theta^m$,

$$\underline{\Delta\Delta} \stackrel{\text{def}}{=} \left(\underline{\gamma_{mf}} - \underline{\gamma_{nf}}\right) - \left(\underline{\gamma_{mb}} - \underline{\gamma_{nb}}\right) = \underline{\gamma_{nb}} - \underline{\gamma_{mb}} (D4.17)$$
$$= \frac{\underline{\gamma_{nb}}}{1+\theta^m}(\theta^m - \theta^n) \; < 0 \; if \; \theta^n > \theta^m \; (D4.18)$$

In addition, the minority-non-minority rating gap between fintech lenders and banks in terms of the conditional expectation of the rating level is,

$\mathbb{E}(\Delta\Delta|\cdot) \stackrel{\text{def}}{=} (1-\delta)(1-\alpha)\left[\mathbb{E}\left(x \middle| x \geq \underline{\gamma_{mf}}, \mu^m, \sigma^m\right) - \mathbb{E}\left(x \middle| x \geq \underline{\gamma_{nf}}\right)\right] - \left[\alpha\mathbb{E}\left(x \middle| x \geq \underline{\gamma_{mb,r}}, \mu^m, \sigma^m\right) + \right.$
$\left.\delta(1-\alpha)\mathbb{E}\left(x \middle| x \geq \underline{\gamma_{mb,nr}}, \mu^m, \sigma^m\right) - \alpha\mathbb{E}\left(x \middle| x \geq \underline{\gamma_{nb,r}}\right) - \delta(1-\alpha)\mathbb{E}\left(x \middle| x \geq \underline{\gamma_{nb,nr}}\right)\right]$

$$= (1-\delta)(1-\alpha)\left[\mathbb{E}\left(x \middle| x \geq \underline{\gamma}, \mu^m, \sigma^m\right) - \mathbb{E}\left(x \middle| x \geq \underline{\gamma}, \mu^n, \sigma^n\right)\right] - \left[\alpha\mathbb{E}\left(x \middle| x \geq \frac{\underline{\gamma}}{1+\theta^m}, \mu^m, \sigma^m\right) + \delta(1-\alpha)\mathbb{E}\left(x \middle| x \geq \underline{\gamma}, \mu^m, \sigma^m\right) - \alpha\mathbb{E}\left(x \middle| x \geq \frac{\underline{\gamma}}{1+\theta^n}, \mu^n, \sigma^n\right) - \delta(1-\alpha)\mathbb{E}\left(x \middle| x \geq \underline{\gamma}, \mu^n, \sigma^n\right)\right] \quad (D4.19)$$

Suppose the underlying rating distribution is the same for minority and non-minority borrowers, i.e., $\mu^m = \mu^n = \mu$ and $\sigma^m = \sigma^n = \sigma$,

$$\mathbb{E}(\Delta\Delta|\cdot) = \alpha\mathbb{E}\left(x \middle| x \geq \frac{\underline{\gamma}}{1+\theta^n}, \mu, \sigma\right) - \alpha\mathbb{E}\left(x \middle| x \geq \frac{\underline{\gamma}}{1+\theta^m}, \mu, \sigma\right) = \alpha\left(h\left(\frac{\underline{\gamma}}{1+\theta^n}\right) - h\left(\frac{\underline{\gamma}}{1+\theta^m}\right)\right) \quad (D4.20)$$

Where $h(x) = \frac{\varphi(x)}{1-\Phi(x)}$ is the hazard function of normal distribution and is increasing in *x*.

If non-minority borrowers are associated with a higher value of lending relationships ($\theta^n > \theta^m$), we have $h\left(\frac{\underline{\gamma}}{1+\theta^n}\right) < h\left(\frac{\underline{\gamma}}{1+\theta^m}\right)$, and thus the minority-non-minority rating gap between fintech lenders and banks in terms of the conditional expectation of the rating level $\mathbb{E}(\Delta\Delta|\cdot) < 0$.

Result Summary – Lending Relationship (Race-Biased). In the case where the payoff function depends on the borrower's rating as well as a race-biased additional utility gain from banks for the subset of borrowers with previous lending relationships, the equilibrium is race-asymmetry in matching rating thresholds. Because the racial group of borrowers associated with a higher value of lending relationships considers the compensational gain from lending relationships larger, they are willing to offer a higher price to banks. Given the price offered by the marginal borrower is the same, that racial group has a smaller matching rating threshold for borrowers with lending relationships. For borrowers not possessing lending relationships, their outside option is the same, and thus the matching rating threshold, in equilibrium, is the same for minority and non-minority borrowers, either using fintech lenders or banks.

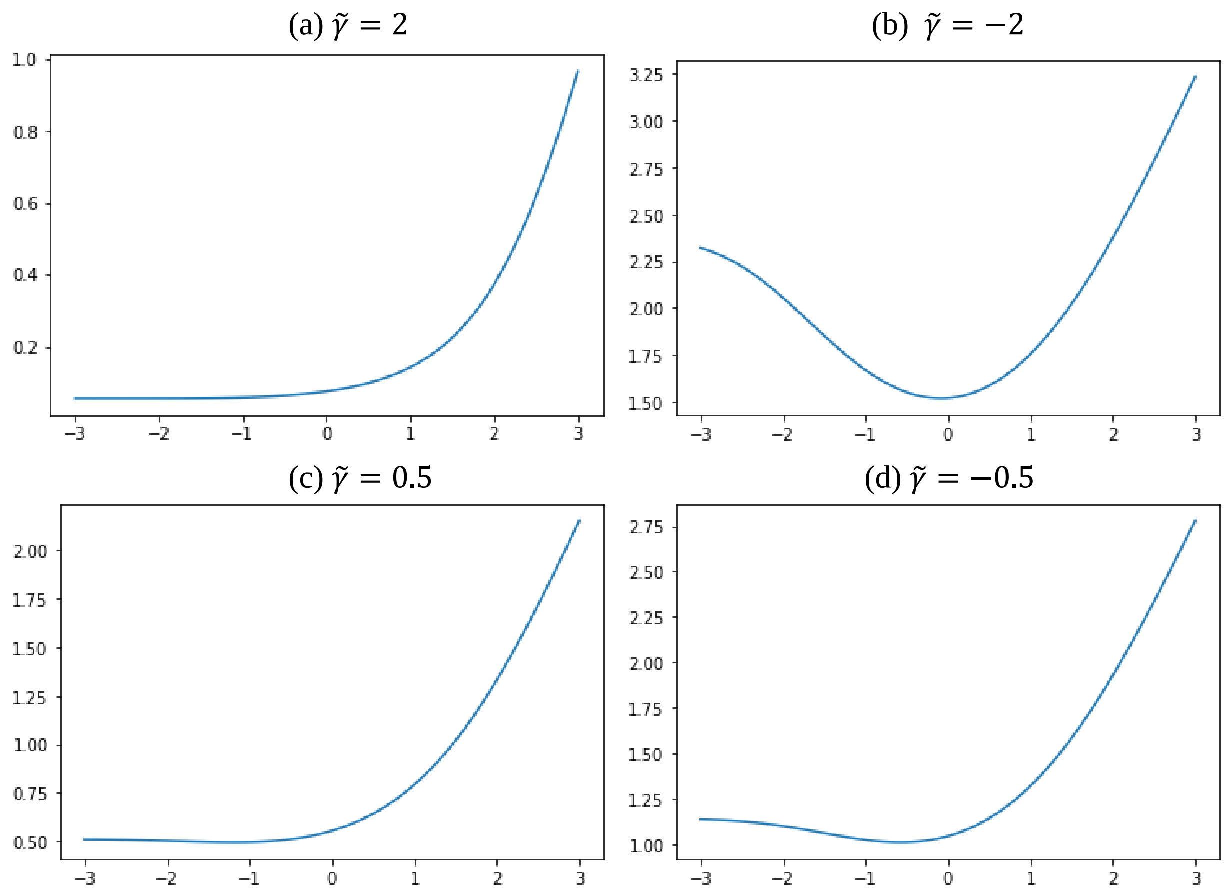
In this case, we also have the result that the racial bias in the payoff function can be translated into a difference in the minority-non-minority rating gap between fintech lenders and banks in terms of the matching thresholds. This difference in the rating gap endogenously affects the share and average rating of matched borrowers with fintech lenders and banks, even without an ex-ante difference in lending relationships between minority and non-minority borrowers.

5. The conditional expectation in the race-biased tech preference case

One thing to notice in the race-biased tech preference case is that the relative mass of borrowers to lenders of each type determines the position of the matching rating thresholds. This in turn determines the sign of the difference in the rating gap in terms of the conditional expectation in Corollary 1. For the G() function in Corollary 1,

$$G(x) = \frac{\varphi(x)}{\Phi(-x)} + \frac{\varphi(x) - \varphi(\tilde{\gamma})}{\Phi(x) - \Phi(\tilde{\gamma})} \quad (D5.1)$$

Because for normal distribution, the hazard rate $\frac{\varphi(x)}{\Phi(-x)}$ is increasing in x, and $\frac{\varphi(x)-\varphi(\tilde{\gamma})}{\Phi(x)-\Phi(\tilde{\gamma})}$ is decreasing in x, the shape of $G(x)$ depends on the value of $\tilde{\gamma}$ which is determined by the relative mass of borrowers to lenders.



Consider the most real-world relevant case where fintech lenders capture a small fraction of the market for both minority and non-minority borrowers and thus $\underline{\gamma_{mf}}$ and $\underline{\gamma_{nf}}$ are above the mean of the rating distribution. Then, $G(x)$ is increasing in x and we have a more negative difference in the minority-non-minority rating gap between fintech lenders and banks in terms of the expected mean of ratings for matched pairs if minority borrowers prefer fintech lenders to banks more than non-minority borrowers.

Appendix E Minority and Fintech Shares in the PPP – Figures and Analysis

We look at the minority and fintech loan shares in the PPP program independently. Figures E1(a) and E1(b) in the upper row plot the percentage of PPP loans, in terms of the sum of loan amounts, disbursed to minority borrowers in each state in 2020 and 2021 respectively. The variation in the minority share across states is very limited in both years, which implies that comparing the geographic variation in minority shares per se might underestimate the minority-non-minority disparities in the PPP program.

[INSERT FIGURE E1 AROUND HERE]

Figures E1 (c) and E1 (d) in the lower row plot the geographic variation in the percentage of PPP loans delivered by fintech lenders across states in the 2020 and 2020 waves correspondingly. The fintech shares are similar across states in 2020, probably due to the much higher credit demand of borrowers of all types in 2020 than in 2021. The cross-state variation is more significant in 2021 and is closer to previously documented evidence (e.g., Buchak et al. (2018) for mortgage origination, Di Maggio and Yao (2021) for consumer loans, CBinsights (2021) for the amount of equity funding into fintech startups). For example, hometowns of earlier fintech lenders such as New York (19.02%) and California (22.25%) have higher fintech usage than surrounding states. Fintech lenders are also more popular in states where new top-funded fintech startups are located, such as Texas (25.43%) and Georgia (27.66%). One exception is Florida which has a fintech share increasing from 11% in 2020 to 35% in 2021, probably because of the surge in COVID-19 cases. Similar plots using the total number of loans instead of the amount of loans are presented in Figure E2.

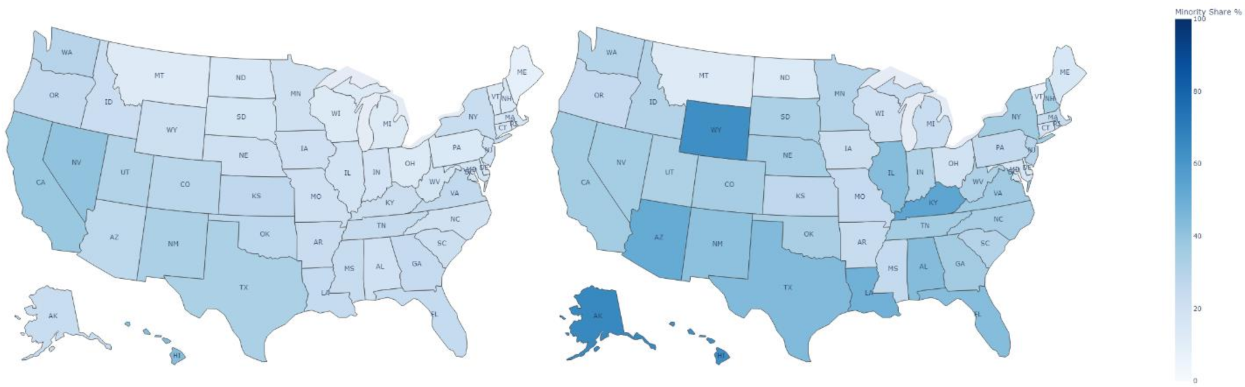
[INSERT FIGURE E2 AROUND HERE]

That the geographic variation in fintech shares does not coincide with the variation in minority shares suggests that fintech lenders are matched with minority versus non-minority borrowers in different magnitudes. There are potentially some underlying differences between the minority borrowers matched with fintech and non-fintech lenders, as we investigate in the regression analysis.

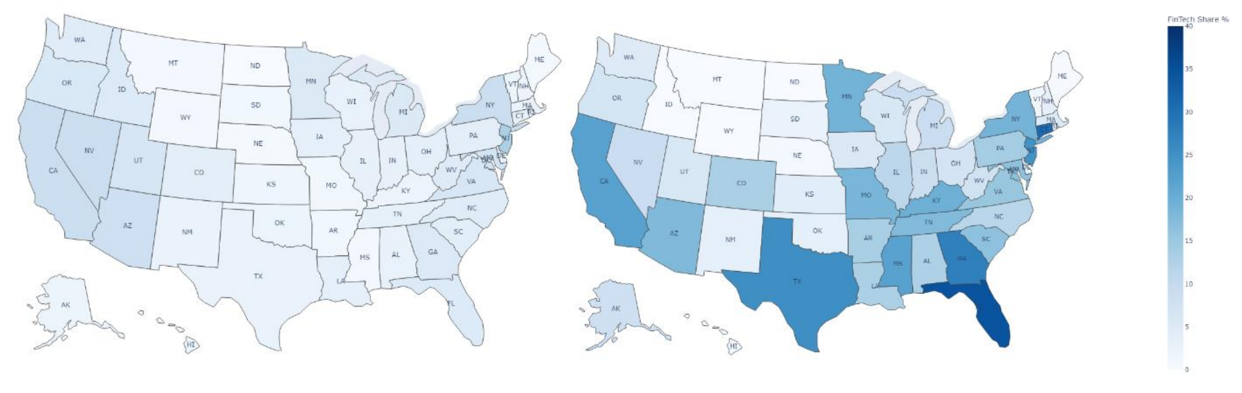
Buchak, G., Matvos, G., Piskorski, T. and Seru, A., 2018. Fintech, regulatory arbitrage, and the rise of shadow banks. *Journal of Financial Economics*, 130(3), pp.453-483.

CBinsights, 2021. The United States of Fintech Startups.

Di Maggio, M. and Yao, V., Fintech Borrowers: Lax Screening or Cream-Skimming?, *The Review of Financial Studies*, Volume 34, Issue 10, October 2021, Pages 4565–4618,



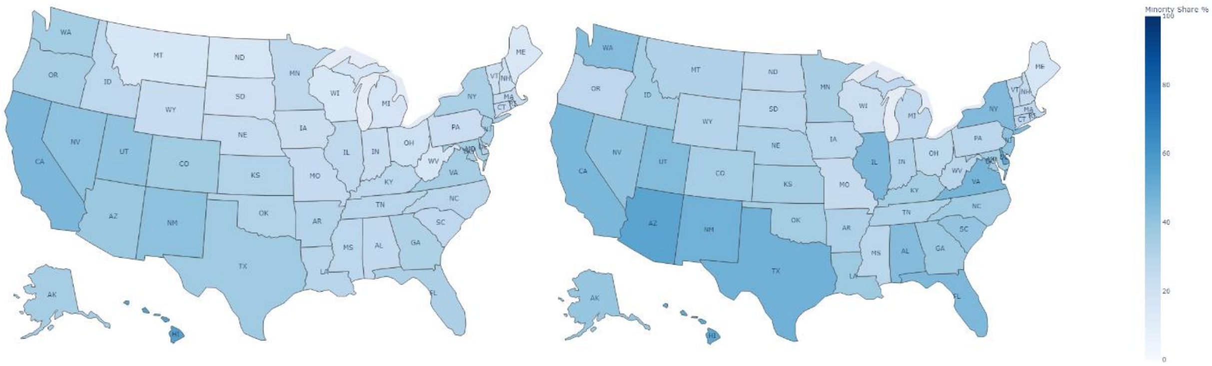
(a) Minority Share in the 2020 PPP (b) Minority Share in the 2021 PPP



(c) Fintech Share in the 2020 PPP (d) Fintech Share in the 2021 PPP

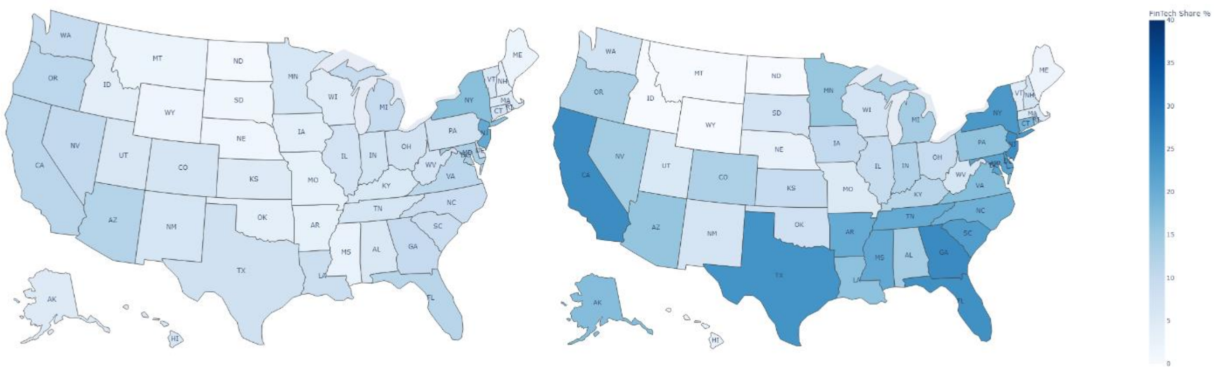
Figure E1 Percentage of Loans Distributed to Minorities (Amount)

This figure plots the share of loan amounts (USD) distributed to minority-owned businesses processed by fintech lenders in the 2020 (panel (a)) and in the 2021 (panel (b)) waves, and the share of loan amounts (USD) in the 2020 (panel (c)) and the 2021 (panel (d)) waves, based on our sample of. The *Minority Shares* range from 0% (the lightest blue) to 100% (the darkest blue).The *FinTech Shares* range from 0% (the lightest blue) to 40% (the darkest blue).



(a) Minority Share (Total) in 2020 PPP

(b) Minority Share (Total) in 2021 PPP



(c) Fintech Share in 2020 PPP

(d) Fintech Share in 2021 PPP

Figure E2 Percentage of Loans Distributed to Minorities (Number)

This figure plots the share of the number of loans distributed to minority-owned businesses in the 2020 PPP program (panel (a)) and in the 2021 PPP program (panel (b)), and the share of loan amounts (USD) processed by fintech lenders in the 2020 PPP program (panel (c)) and the 2021 PPP program (panel (d)), based on our sample. The *Minority Shares* range from 0% (the lightest blue) to 100% (the darkest blue). The *FinTech Shares* range from 0% (the lightest blue) to 40% (the darkest blue).